2014

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Ice cloud detection from AMSU-A, MHS, and HIRS satellite instruments inferred by cloud profiling radar

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(Received 1 July 2014; accepted 16 November 2014)

An algorithm for ice cloud detection aided by support vector machine (AID-SVM) is presented. The AID-SVM algorithm is applied and tested for the Advanced Microwave Sounding Unit-A, microwave humidity sounder (MHS), and high resolution infrared radiation sounder (HIRS) instruments onboard NOAA-19 satellite. The algorithm is based on satellite brightness temperature measurements and developed as well as validated by using collocated ice/no-ice cloud information acquired from the CloudSat cloud-profiling radar. The algorithm is tested over both ocean and land surfaces. Overall, the results exhibit very promising potential to acquire ice/no-ice cloud information using the passive satellite sensors. It is found that infrared satellite sensor such as HIRS is more efficient in detecting ice clouds than the counterpart microwave satellite sensors. Furthermore, the combined measurements using microwave/infrared synergy perform no better than the infrared-only measurements.

1. Introduction

The detection of ice clouds is imperative for a variety of reasons within the atmospheric sciences domain. First, the ice clouds carry significant role in global atmosphere, mainly, because of its radiative influence on earth's energy balance (Koop 2013; Yamada and Satoh 2013; Gao, Li, and Zhou 2014). Second, ice clouds regulate the forecasting applications and have an influence on climate change (Delanoe et al. 2011; Protat et al. 2011; Jin et al. 2014). Better detection of ice clouds will lead to better weather and climate forecasts. Third, accurate detection of ice clouds is a necessary step in satellite remote sensing, and subsequently, the retrieval of geophysical parameters as ice clouds can impact the quality of such retrieval (Østby, Schuler, and Westermann 2014).

Over the past years, a wide range of satellite instruments has been deployed to enable the observations of global coverage of ice clouds. Given the importance of ice cloud properties in the Earth's energy budget, such satellite studies of ice clouds continue to be an area of active research. Particularly, progresses have been made on both microwave (MW) and infrared (IR) remote sensing-based cloud detection algorithms (Inoue et al. 2010; Sreerekha, Doherty, and English 2010; Wind et al. 2010; He 2011; Yoo and Li 2012; Hutchison, Iisager, and Mahoney 2013; Millán et al. 2013). Generally speaking, most of the algorithms employ threshold-based criteria to distinguish between cloudy and clear pixels. Despite the progress, it is also to be remembered that there are intrinsic limitations to the passive satellite observations for ice cloud studies (Liu et al. 2010). Passive satellite sensors cannot sense the full vertical structure

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of a storm as active sensors can do. Consequently, in passive remote sensing-based ice cloud algorithms, vertical cloud homogeneity are assumed, which may lead to erratic outputs.

To overcome the above limitations, CloudSat satellite carrying a millimeter wavelength cloud profiling radar (CPR) was launched to join the A-train satellite constellation in 2006 (Stephens et al. 2002). The primary purpose of the CloudSat satellite is to study clouds and precipitation from space. In fact, cloud radar can potentially detect those sensitive clouds, which remain undetected by passive satellite measurements. However, CloudSat's area coverage is limited. As a fact, in addition to the cloud radar, the use of passive satellite measurements is essential for enhancing the temporal and spatial resolutions of ice cloud products.

In this study, we propose an ice cloud detection algorithm for passive satellite sensors at MW/IR frequencies. The proposed algorithm will be based on support vector machine (SVM). The algorithm, hereinafter named as an algorithm for ice cloud detection aided by SVM (AID-SVM), will be trained in such a way that the passive remote sensing-based output is in consistent with the CloudSat radar ice/no-ice cloud observations. The combined use of MW/IR observations will also be investigated in determining whether they are able to improve the detection capability.

2. Data

The reference radar data sets used in this work are from the CPR-derived radar-only ice water path (IWP) information stored in 2B-CWC-RO product according to the algorithm described in Austin, Heymsfield, and Stephens (2009). In contrast, the passive satellite data are from the Advanced Microwave Sounding Unit (AMSU)-A, microwave humidity sounder (MHS), and high resolution infrared radiation sounder (HIRS) instruments onboard NOAA-19 satellite (see Tables 1–2 for the radiometric characteristics). It is to be noted that the former two sensors are MW radiometers, whereas the later sensor gathers visible and IR radiometric observations. The AMSU-A measures the MW radiation with 15 radiometric channels between 23 and 50 GHz using cross-track scanning strategy. Similar to the AMSU-A, MHS is a five-channel cross-track radiometer with three channels in the water vapour absorption line (183.31 GHz) along with two window channels (89 and 150 GHz). On the other hand, the HIRS instrument is operated in 20 channels, including 1 visible and 19 IR channels.

Table 1. Radiometric characteristics of the AMSU-A (1–15) and MHS (16–20) channels.

Channel number	Frequency (GHz)	Polarization	Number of bands	Instrument sensitivity (K)
1	23.8	V	1	0.30
2	31.4	V	1	0.30
3	50.3	V	1	0.40
4	52.8	V	1	0.25
5	53.596 $\pm$ 0.115	H	2	0.25
6	54.4	H	1	0.25
7	54.94	V	1	0.25
8	55.5	H	1	0.25
9	57.290	H	1	0.25
10	57.290 $\pm$ 0.217	H	2	0.40
11	57.290 $\pm$ 0.3222 $\pm$ 0.048	H	4	0.40
12	57.290 $\pm$ 0.3222 $\pm$ 0.022	H	4	0.60
13	57.290 $\pm$ 0.3222 $\pm$ 0.010	H	4	0.80
14	57.290 $\pm$ 0.3222 $\pm$ 0.0045	H	4	1.20
15	89.0	V	1	0.50
16	89.0	V	1	0.22
17	157.0	V	1	0.34
18	183.311 $\pm$ 1.00	H	2	0.51
19	183.311 $\pm$ 3.00	H	2	0.40
20	190.311	V	1	0.46

Table 2. Radiometric characteristics of the HIRS channels.

Channel	Centre wave number (cm ⁻¹)	Centre frequency (mm)	Half bandwidth (cm ⁻¹)	Anticipated maximum scene temperature (K)	Specified NEDN (mW/m ² /sterad/cm ⁻¹)
1	668.5 ± 1.3	14.959	3.0 + 1/-0.5	280	3.00
2	680.0 ± 1.8	14.706	10.0 + 4/-1	265	0.67
3	690.0 ± 1.8	14.493	12.0 + 6/-0	240	0.50
4	703.0 ± 1.8	14.225	16.0 + 4/-2	250	0.31
5	716.0 ± 1.8	13.966	16.0 + 4/-2	265	0.21
6	733.0 ± 1.8	13.643	16.0 + 4/-2	280	0.24
7	749.0 ± 1.8	13.351	16.0 + 4/-2	290	0.20
8	900.0 ± 2.7	11.111	35.0 ± 5.0	330	0.10
9	1030.0 ± 4.0	9.709	25.0 ± 3.0	270	0.15
10	802.0 ± 2.0	12.469	16.0 + 4/-2	300	0.15
11	1365.0 ± 5.0	7.326	40.0 ± 5.0	275	0.20
12	1533.0 ± 2/-6	6.523	55.0 ± 5.0	255	0.20
13	2188.0 ± 4.4	4.570	23.0 ± 3.0	300	0.006
14	2210.0 ± 4.4	4.525	23.0 ± 3.0	290	0.003
15	2235.0 ± 4.4	4.474	23.0 ± 3.0	280	0.004
16	2245.0 ± 4.4	4.454	23.0 ± 3.0	270	0.004
17	2420.0 ± 4.0	4.132	28.0 ± 3.0	330	0.002
18	2515.0 ± 5.0	3.976	35.0 ± 5.0	340	0.002
19	2660.0 ± 9.5	3.759	100.0 ± 15.0	340	0.001
20	14,500 ± 220	0.690	1000 ± 150.0	100% Albedo.	0.10% Albedo

To develop the ice cloud detection algorithms for passive satellite radiometers, that will be consistent with the CloudSat ice cloud detection, it requires bringing the radiometric and CloudSat ice cloud information in the same domain. Therefore, for the sake of analysis, a testbed database is constructed comprising of radiometric and CPR IWP collocation samples collected from a wide range of meteorological events, according to Holl et al. (2010). The collocation database is restricted to latitudes within 25° of the equator. This is mainly done for minimizing the radiometric scattering coming from the surface. Over the tropics, the atmosphere is very humid. The band of extreme water vapour concentrations would inhibit the radiometers to receive signals from the surface. Further, the collocation database is subdivided into two groups to form calibration and validation data sets, respectively, for training and testing purpose.

3. Detection algorithm

Machine learning algorithms have received increasing interest in recent years within the remote sensing community (Islam, Rico-Ramirez, and Han 2012; Islam et al. 2013; Srivastava, Han, Rico-Ramirez, et al. 2013; Islam, Srivastava, et al. 2014). In this study, the proposed ice cloud detection algorithm is based on a machine learning algorithm, the SVM (Srivastava et al. 2012; Srivastava, Han, Ramirez, et al. 2013), in which the inputs are the radiometric brightness temperatures (T_B), whereas the output is the ice/no-ice cloud properties.

Theoretically, our classification is a supervised binary classification problem. Let us consider the training set consists of N vector samples from a d -dimensional feature space, where $x_i \in \mathbb{R}^d (i = 1, 2, \dots, N)$. For each vector x_i , a target $y_i \in \{-1, 1\}$ is given. If the two classes are linearly separable, it would be straightforward to find a hyperplane between two classes defined by a vector $\mathbf{w} \in \mathbb{R}^d$ and a bias $b \in \mathbb{R}$. The membership decision rule is based on the signum function $\text{sgn}[f(x)]$:

$$f(x) = \mathbf{w} \cdot \mathbf{x} + b \quad (1)$$

where $f(x)$ denotes the discriminant function associated with the hyperplane. The $\mathbf{w}$ and b are estimate in such a way that

$$y_i(\mathbf{w} \cdot x_i + b) > 0, \quad i = 1, 2, \dots, N \quad (2)$$

The optimal hyperplane is determined by maximizing the separating margin such that

$$\min_{i=1,2,\dots,N} y_i(\mathbf{w} \cdot x_i + b) \geq 1 \quad (3)$$

The above linearly constrained optimization problem can be formulated using a Lagrangian function:

$$\max_{\alpha} \sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i,j=1}^N \alpha_i \alpha_j y_i y_j K(x_i, x_j) \quad (4)$$

where

$$\sum_{i=1}^N \alpha_i y_i = 0 \quad (5)$$

and

$$\alpha_i \geq 0, \quad i = 1, 2, \dots, N \quad (6)$$

where α is the vector of Lagrange multipliers, which can be obtained using quadratic programming methods. Consequently, the discriminant function is formed as

$$f(x) = \sum_{i \in S} \alpha_i y_i (x_i \cdot x) + b \quad (7)$$

where S is the subset of indices corresponding to non-zero α_i 's. These indices are known as support vectors.

In the case of linearly non-separable data, a cost function is minimized using margin maximization and error minimization terms:

$$\Psi(\mathbf{w}, \xi) = \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^N \xi_i \quad (8)$$

where the ξ_i are known as slack variables and C as the penalty parameter. The minimization of the above cost function is under the following constraints:

$$y_i(\mathbf{w} \cdot x_i + b) > 1 - \xi_i, \quad i = 1, 2, \dots, N \quad (9)$$

and

$$\xi_i \geq 0, \quad i = 1, 2, \dots, N \quad (10)$$

For further improving the separation, a Kernel function can be introduced. However, in this study, a linear SVM is implemented. The penalty parameter C is taken as 1. It is important to stress out that the minimum detectable cloud reflectivity by the CPR is around -26 dBZ, leading to an IWP detection limit of 1 g m^{-2} (Austin, Heymsfield, and Stephens 2009; Holl et al. 2010). Considering this, a threshold of 1 g m^{-2} has been taken as the criteria for the separation of ice/no-ice cloud information, while training the AID-SVM. Five different sensor combinations have been investigated as the input measurements to the AID-SVM algorithm: (1) AMSU-A, (2) MHS, (3) HIRS, (4) AMSU-A + MHS, and (5) AMSU-A + MHS + HIRS radiometric T_B measurements.

4. Results and discussions

Before providing the performance of the proposed AID-SVM algorithm here, we investigate the sensitivity of T_B measurements to ice/no-ice cloud information. As such, a parallel coordinate plot is constructed comprising brightness temperature measurements as input vectors in Figure 1. The significance of parallel coordinate plot is that it can make data visualization easier and comparable for a large number of variables together. Furthermore, informative investigation of higher-dimensional relationships between the variables can be made. In this plot, the horizontal axis signifies the coordinate, and the vertical axis signifies the values. That means, first 15 coordinates are related to 15 AMSU-A channels, followed by 5 MHS and 20 HIRS channels. From the parallel coordinates plot, it can be seen that the ice cloud distributions for the HIRS channels 24–39 are significantly different from the no-ice cloud distributions. This implies that these input measurements are excellent options for ice cloud detection. The MHS channels (16–20) also carry some good skills to classify ice/no-ice cloud information, as the figure suggests. Nevertheless, the distribution margins are somewhat narrower for the AMSU-A coordinates.

For more detailed understanding, Figures 2 and 3 give the probability density function (PDF) estimate of brightness temperatures for ice and no-ice cloud pixels. Figure 2 is for the AMSU-A/MHS channels, whereas Figure 3 is for the HIRS channels. The PDFs are constructed for ocean surface only by considering the data sets from calibration database. The overlaps between the distributions of ice/no-ice clouds are evident for all the channels, either in AMSU-A or in MHS measurements. This implies that no particular frequency is capable of detecting ice clouds perfectly. However, there are some distribution differences between ice/no-ice cloud pixels, in some channels. It is to be noted that the AMSU-A channels 3–14 near oxygen absorption band (60 GHz) are primarily designed to measure atmospheric temperature profiles. On the other hand, AMSU-A/MHS channels 1–2, some other window channels near 89 GHz (15–16), along with ice scattering channels near 183 GHz (18–20) are primarily responsible for measuring cloud and surface properties. Such interpretation can clearly be made from Figure 2. It can be seen that the distribution difference is more pronounced for the cloud sensitive channels than the temperature sounding channels. On the other hand, a good distribution difference exists for the HIRS measurements in channels 4–20 (Figure 3).

Overall, based on the parallel coordinate and histogram plots, one should anticipate that HIRS will have better skills in detecting ice/no-ice cloud information than the AMSU-A instrument. In the latter section, we will be scrutinizing, if this is the case. We will also investigate whether the synergistic MW/IR measurements would improve the results in detecting the ice clouds than either the MW or IR measurements on their own. As a reference, in Figure 4, we plot the bivariate histogram distribution of T_B between MHS 183 ± 3 GHz and HIRS $12.47 \mu\text{m}$ for ice

Figure 1. Parallel coordinate plot of brightness temperature measurements for no-ice cloud and ice cloud pixels: ocean (left) and land (right). The coordinates 1–15 represent the AMSU-A channels, followed by the 5 MHS channels, and the 20 HIRS channels. The median and quartiles (25% and 75% points) are also shown as dotted outlines.

Figure 2. PDF histograms of brightness temperature measurements (K) for the AMSU-A (1–15) and MHS (16–20) channels.

and no-ice cloud pixels. The differences between the distributions are somewhat noticeable. This gives us confidence that both MW and IR measurements will be able to detect ice clouds.

Table 3 summarizes the standard categorical and verification scores of ice cloud detection for the AMSU-A, MHS, HIRS, AMSU-A + MHS, and AMSU-A + MHS + HIRS sensor combinations in comparison with CloudSat CPR observations (using 1 g m^{-2} as detection threshold). The scores are computed using the AID-SVM model applied to the validation database. The following categorical scores are used for the assessment—accuracy, frequency bias, probability of detection, false alarm ratio, probability of false detection, success ratio, critical success index, equitable threat score, Hansen–Kuipers discriminant, odds ratio, and Yule’s Q. The basis of the categorical scores is a contingency table, tabulating the agreement and disagreement between the forecast and observations data sets. More information regarding the calculation of the scores can be found in Islam et al. (2012) and Islam, Rico-Ramirez, et al. (2014).

Overall, the categorical scores obtained by the AID-SVM model are very promising. However, the ability to capture accurate ice cloud pixels is rather sensor-dependent. It can be seen that the IR sensor HIRS performs better than the MW instruments AMSU-A and MHS. For instance, over the ocean, the CSI is calculated as 0.68 by the HIRS instrument, whereas, by using the AMSU-A and MHS sensors, respectively, the CSI scores are only 0.32 and 0.45. Similar conclusions can be made based on other categorical scores. Besides, as indicated by the categorical scores, this is also true over the land surface. Of course, the scores are somewhat decreased over land from the ocean surface, most likely because of non-uniform emissivity of the land surface, which is to be expected. As an example, the CSI score is reduced from 0.68 (ocean) to 0.59 (land) for the HIRS sensor-based ice cloud detection. It is not unexpected that the HIRS sensor outperforms the counterpart MW sensors in detecting ice clouds. The measurements at IR channels are known to be strongly sensitive to thin ice clouds,

Figure 3. PDF histograms of brightness temperature measurements (K) for the HIRS channels.

Figure 4. The bivariate histograms of brightness temperature measurements (K) between MHS 183 ± 3 GHz and HIRS $12.49 \mu\text{m}$ channels: no ice cloud (left) and ice cloud conditions (right).

as reported by many authors (Aires et al. 2011; Stein, Delanoë, and Hogan 2011; Kahn et al. 2014). Therefore, the information content obtained from IR-based measurements can add valuable skills towards ice cloud detection. In contrast, in comparison to IR observations, MW measurements are somewhat less sensitive to thin ice clouds. That is why the AMSU-A and MHS are found to be less skillful for ice cloud detection than the HIRS measurements. Nonetheless, MW measurements have the capability of propagating through the clouds, whereas IR measurements are mainly sensitive to the radiation emitted or scattered from top of the atmosphere. As such, the MW measurements are better capable of sensing the total cloud layer information, thus providing better retrieval of cloud intensity instead (e.g., cloud water contents) than the detection. One more important point to note is that the MHS has better detection capability than AMSU-A instrument, as the table demonstrates. This is mainly

Table 3. Statistical analysis of results of ice cloud detection as predicted by the AID-SVM model.

		Accuracy	Frequency bias	Probability of detection	False alarm ratio	Probability of false detection	Success ratio	Critical success index	Equitable threat score	Hansen– Kuipers discriminant	Odds ratio	Yule’s Q
Ocean	AMSU/A	0.72	0.54	0.37	0.31	0.09	0.69	0.32	0.18	0.28	5.71	0.70
	MHS	0.81	0.63	0.51	0.20	0.05	0.80	0.45	0.34	0.45	18.05	0.89
	HIRS	0.93	1.04	0.83	0.20	0.05	0.80	0.68	0.62	0.78	92.56	0.98
	AMSU/A + MHS	0.81	0.71	0.51	0.29	0.08	0.71	0.42	0.31	0.43	12.55	0.85
Land	AMSU/A + MHS + HIRS	0.93	1.05	0.83	0.21	0.05	0.79	0.67	0.61	0.78	89.20	0.98
	AMSU/A	0.73	0.81	0.42	0.48	0.15	0.52	0.30	0.17	0.27	4.19	0.61
	MHS	0.77	0.68	0.50	0.27	0.09	0.73	0.42	0.28	0.41	9.96	0.82
	HIRS	0.89	1.04	0.76	0.28	0.08	0.72	0.59	0.50	0.68	36.85	0.95
	AMSU/A + MHS	0.73	0.57	0.45	0.21	0.08	0.79	0.40	0.25	0.37	9.63	0.81
	AMSU/A + MHS + HIRS	0.88	1.29	0.80	0.38	0.10	0.62	0.54	0.45	0.70	34.89	0.94

because the scattering phenomenon on ice particles is more dominant at higher frequencies (MHS channels) than at lower frequencies (AMSU-A channels). At lower frequencies, more specifically, below 80 GHz, MW radiation is less impacted by the occurrence of ice clouds. The lower frequency measurements are mainly exposed to emission and absorption by liquid clouds. According to our results from Table 3, it is also to be noted that the synergistic MW/IR measurements perform no better than the IR-only measurements. In fact, the relative performance between the HIRS only and AMSU-A + MHS + HIRS combination is comparable.

5. Summary

In this article, a new ice detection algorithm (AID-SVM) is introduced for the AMSU-A, MHS, and HIRS passive satellite sensors. The algorithm is based on SVM and uses only satellite brightness temperature measurements as input vectors. The proposed AID-SVM algorithm is complemented by CloudSat CPR ice cloud observations, which are collocated to the passive satellite sensors to calibrate as well as validate the algorithm. The algorithm is found to perform reasonably well in positively identifying ice clouds over both ocean and land surfaces. In particular, it is exhibited that HIRS measurements have better capability in effectively discriminating no-ice/ice cloud information than the AMSU-A or MHS measurements.

Acknowledgements

The authors acknowledge the NASA CloudSat project. The views expressed here are those of the authors solely and do not constitute a statement of policy, decision, or position on behalf of NOAA, NASA, or the authors' affiliated institutions.

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