Storm Classification and Dynamic Targeting for a SMart ICE Cloud Sensing (SMICES) Satellite

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Motivation

Smart Ice Cloud Sensing (SMICES) is a small-sat concept in which a radar intelligently targets ice-storms based on information collected by a lookahead radiometer. Often space observations are performed by continuously collecting data from an instrument aimed at nadir (e.g. directly below the satellite). However, an intelligent scheme can improve science return if the platform can assess the science utility of the features along its path. In the case of SMICES, power constraints and the rarity of storms means that blind nadir targeting would collect a limited amount of storm data. The work proposed acquires measurements to maximize acquired high interest storms while concurrently collecting a background sampling of all features. This is accomplished through two steps: storm classification and dynamic targeting. For classification we describe a multi-step use of Machine Learning and Digital Twin of Earth's atmosphere to create a classifier. We discuss an autonomous data labelling pipeline to label the cloud types in the datasets. The data is then used to train five different models to identify storms in tropical and non-tropical regions, and assess the results. For dynamic targeting six algorithms ranging from "blind" to more selective are described and evaluated on their improvement over "blind" targeting.

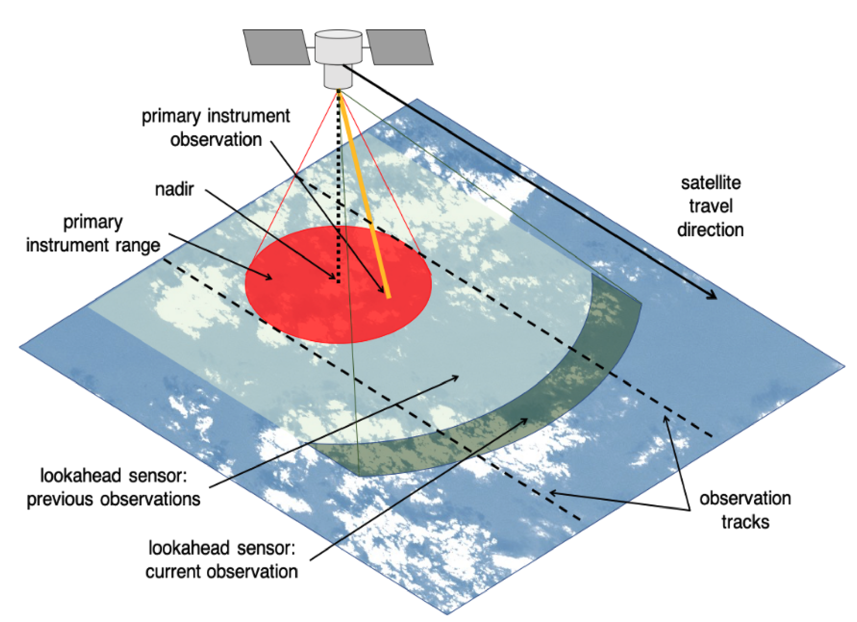

Figure 1. Example of SMICES concept in flight

Datasets

Two regional datasets were used in this work: tropical and non-tropical. Both datasets were created through the Global Weather Research and Forecasting (GWRF) model [3]. The model generated the brightness temperatures for different cloud types along eight bands of radiance as well as the scientific variables of ice water path, median particle size, and median cloud top height. Cloud labels were generated through an autonomous data labelling pipeline which utilized K-means clustering. The mapping of clusters to labels is shown in figure 3.

	Clear, Thin Cirrus, and Cirrus	Rainy Anvil	Convection Core
Clear, Thin Cirrus, and Cirrus	44226 88.38%	5751 11.49%	63 0.13%
Rainy Anvil	3858 16.55%	19043 81.70%	408 1.75%
Convection Core	109 12.02%	584 64.39%	214 23.59%

	Clear, Thin Cirrus, and Cirrus	Rainy Anvil	Convection Core
Clear, Thin Cirrus, and Cirrus	3539649 89.61%	246916 6.25%	163505 4.14%
Rainy Anvil	254077 46.25%	196388 35.75%	98939 18.01%
Convection Core	273330 76.85%	38958 10.95%	43378 12.20%

Figure 2. Confusion matrices of the RDF classifier on the tropical (left) and non-tropical (right) dataset, max depth 14, number of trees 32, weights equalized by class

Approach

The SMICES classification problem is to correctly classify storms utilizing the information the on-board radiometer collects and then target the storms with a radar instrument. The classifier needs to be able to correctly identify five different cloud types: clear, thin cirrus, cirrus, rainy anvil, and convection core. The convection core and rainy anvil clouds are both considered storms with convection core having more scientific value.

The SMICES problem is a continuous online planning problem implemented as an orbiting satellite where there is no set end to the imaging of the clouds. The parameters include an orbiting altitude of 400km and the setup is designed to allow its radar to slew 15° from nadir in all directions. The slewing is assumed to have instantaneous electronic movement. The radar is capable of targeting an area of roughly 4x4km whenever it is turned on. The power constraints of the vehicle mean that the targeting should reach a 20% duty cycle at any given time over the course of the flight.

Hidden values by cluster

Cluster Color	IWP (mean: std)	Median Particle Size (mean: std)	Median Cloud Top Height (mean: std)	Assigned Cloud Type
Yellow	0: 0	0: 0	0: 0	Clear
Orange	.98: 12.9	37.2: 16.5	11,794: 1,290	Thin Cirrus
Green	55.2: 197	103: 37.9	7,412: 787	Cirrus
Red	473: 806	270: 169	4,870: 573	Rainy Anvil
Purple	8,476: 4,312	539: 155	4,539: 652	Convection Core

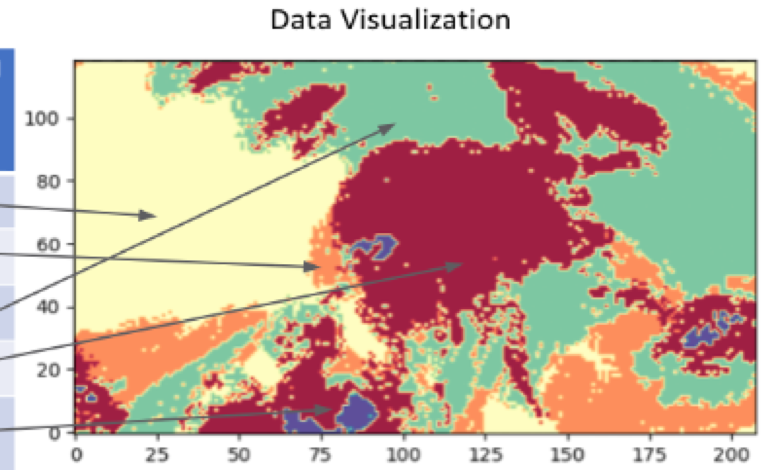

Figure 3. Cluster values mapped to their labels on the tropical dataset

Classification

For this study we explored the following classifiers: random decision forest (RDF), support vector machine (SVM), Gaussian Naïve Bayesian, a feed forward artificial neural network (ANN), and a convolutional neural network (CNN). The neural networks were run as single pixel classifiers.

Overall the results of the classifiers were promising for distinguishing deep convective storms in the tropical dataset. Further work still needs to be done for finer grained storm discrimination. Deep convective storm identification in the non-tropical dataset was more challenging. The best performing classifier was the random decision forest, which achieved an accuracy of 83% and 42% for identifying storm clouds in the tropical and non-tropical datasets respectively. The confusion matrices are found in Figure 2. This classifier is later utilized in the dynamic targeting experiment.

Dynamic Targeting

The baseline algorithms is a random algorithm which randomly analyzes 20% of the clouds under nadir. Our best performing algorithm, Greedy Smart, utilizes the entire knowledge window (the area from the back of the radar's reachability to the front of the radiometer sweep) and ranks the priority of each storm with preference towards storms closer to nadir. By utilizing the entire knowledge window we are able to improve the gain of capturing convection core clouds by a factor of 24 and rainy anvil clouds by a factor of 2 [4]. Further work on the dynamic targeting concept has been conducted at JPL [1][2]

Dynamic Targeting Results

The total success of SMICES mission is ultimately measured on the improvements dynamic targeting bring to mission return. Our initial dynamic targeting results demonstrate the distribution of pixels we would acquire if the classifier used in the simulation was 100% accurate.

In Figure 4, row 4 of each table shows the distribution of pixels we would acquire if the classifier used in the simulation was 100% accurate. Row 5 shows the distribution of pixels (true labels) we actually acquire, quantifying how classification inaccuracy reduces the impact on return. However, this mode still dramatically outperforms uninformed (random) targeting. This highlights how preferential targeting is able to skew sampled pixels towards storm-cloud classes in both datasets.

	Clear, Thin Cirrus, and Cirrus	Rainy Anvil	Convection Core
Sample Randomly	67.0%	32.0%	1.0%
Sample Labelled as Rainy Anvil	16.6%	81.7%	1.8%
Sample Labelled as Convection Core	12.0%	64.4%	23.6%
Preferential Targeting (as labelled	10.5%	64.2%	25.3%
Preferential Targeting (true labels)	23.2%	69.7%	7.1%

	Clear, Thin Cirrus, and Cirrus	Rainy Anvil	Convection Core
Sample Randomly	67.0%	32.0%	1.0%
Sample Labelled as Rainy Anvil	46.3%	35.8%	18.0%
Sample Labelled as Convection Core	76.9%	10.9%	12.2%
Preferential Targeting (as labelled)	44.6%	21.3%	34.1%
Preferential Targeting (true labels)	76.1%	14.1%	9.8%

Figure 4. Mission return impact of intelligent targeting on the tropical dataset (left) and non-tropical dataset (right)

Future Work and Next Steps

We would like to extend our datasets to more regions beyond the Caribbean and Atlantic coast to improve classifier robustness. Future work on the classifiers will expand beyond single pixel classification to take into account the surrounding pixels. It is important to run the targeting simulation over a dataset that is representative of what SMICES would see in a real flight. Further research needs to be conducted on the impact that off-nadir analysis has on the data quality collected. For more information see: Storm-Classification and Dynamic Targeting for a SMart ICE Cloud Sensing (SMICES) Satellite [5]

Acknowledgements

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References

[1] Alberto Candela, Jason Swope, and Steve Chien. Dynamic targeting to improve earth science missions. *Journal of Aerospace Information Systems (JAIS)*, 20(11):679–689, September 2023. `arXiv:https://doi.org/10.2514/1.I011233`, `doi:10.2514/1.I011233`.

[2] Steve Chien, Alberto Candela, Juan Delfa, Akseli Kangaslahti, and Abigail Breitfeld. Expanding and maturing dynamic targeting. In *17th Symposium on Advanced Space Technologies in Robotics and Automation (ASTRA 2023)*, October 2023. URL: `https://ai.jpl.nasa.gov/public/documents/papers/DT-Update-ASTRA-2023.pdf`.

[3] Skamarock, W.C., J.B. Klemp, J. Dudhia, Gill, D.O., Z. Liu, J. Berner, W. Wang, G. Powers, M.G. Duda, D.M. Barker, and Huang X.-Y. A description of the advanced research wrf version 4. *NCAR Tech. Note NCAR/TN-556+STR*, page 145 pp., 2019. `doi:10.5065/1dfh-6p97`.

[4] Jason Swope, Steve Chien, Xavier Bosch-Lluis, Qing Yue, Peyman Tavallali, Mehmet Ogut, Isaac Ramos, Pekka Kangaslahti, William Deal, and Caitlyn Cooke. Using intelligent targeting to increase the science return of a smart ice storm hunting radar. In *International Workshop on Planning & Scheduling for Space (IWPSS)*, July 2021. URL: `https://ai.jpl.nasa.gov/public/documents/papers/Swope-SMICES-targeting-IWPSS-2021.pdf`.

[5] Jason Swope, Steve Chien, Xavier Bosch-Lluis, Qing Yue, Peyman Tavallali, Mehmet Ogut, Isaac Ramos, Pekka Kangaslahti, William Deal, and Caitlyn Cooke. Storm-classification and dynamic targeting for a smart ice cloud sensing (smices) satellite. In press at the Journal of Aerosapce Information Systems (JAIS), 2024.

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