German Aerospace Center
in the Helmholtz Association
German Space Operations Center (GSOC)

Real-time Cloud Detection and On-Board Planning for Optimization of the Satellites' Efficiency

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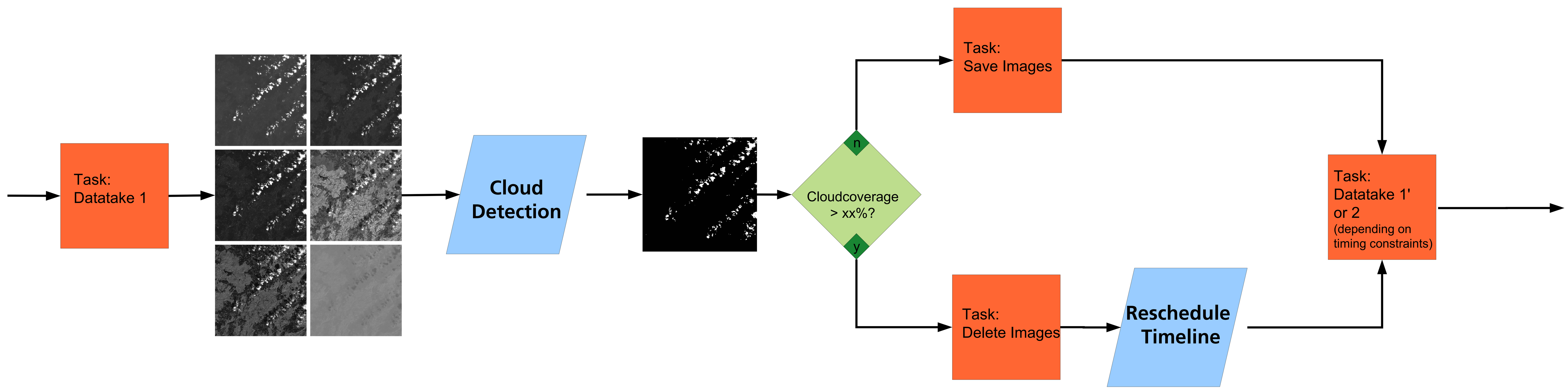
Space Flight Technology

Images of the Earth's surface acquired by remote sensing satellites are stored on-board and transmitted to a ground station when within view. For reducing the amount of data stored and transmitted a first evaluation of the acquired image on board of the satellite in real-time is of interest. This evaluation includes in the first place a cloud detection method and can be followed by e.g. a change detection[1]. Depending on the result of these methods a rescheduling of the on-board timeline can be executed in order to optimize the satellite's usage. If, e.g., the cloud-contamination of a scene exceeds a certain percentage, it can be deleted from the on-board memory and instead another scene can be planned to take its place. Here, the first results of implementations of the cloud detection and the on-board rescheduling are proposed.



Cloud Detection

At any time, about 60% of the Earth is covered by clouds. Therefore a huge amount of scenes captured by satellites is not suitable for remote sensing of the Earth' surface. Hence an important task would be to detect cloud-contaminated scenes and delete them immediately on-board in order to save resources.
The distinction between cloud-contaminated and non-cloud-contaminated scenes can be done by means of supervised learning methods where, given a set of scenes with known labels (cloud, no cloud), each pixel of a new scene can be classified into one of the two categories. Here, this classification task is done by means of Support Vector Machines (SVM).

Theoretical Background

SVMs are used to separate several classes in a dataset. This is done by evaluating the decision function (for two classes)

$$f(\vec{x}) = sgn(\langle \vec{w}, \vec{x} \rangle + b)$$

for each n-dimensional point $\vec{x}$ in the input space. $\vec{w}$ and b describe the hyperplane that separates the two classes. These two parameters are estimated by solving the optimization problem

$$min_{\vec{w},b,\vec{\xi}} \quad \frac{1}{2}\vec{w}^{\,t}\vec{w} + C\sum_i \xi_i$$

$$\text{subject to} \quad y_i(\vec{w}^{\,t}\vec{x}_i + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

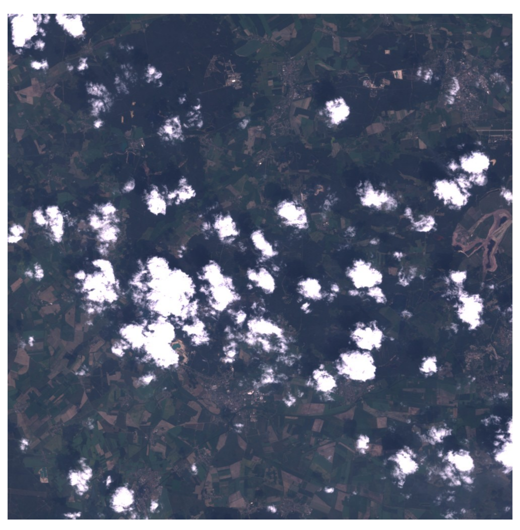
where i is the number of training points and ξ_i are slack variables that measure the degree of misclassification of the training data set. Further information can be found in[2].

Training of the Classificator

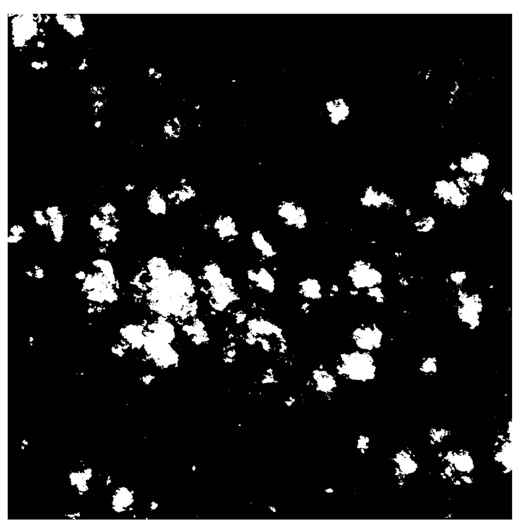
For the training of the classifier 38536 points from 12 different Landsat-7 scenes covering the surfaces water, snow and ice, forest, rural and urban areas, mountains and desert were extracted. Each point is a 5-dimensional array where each dimension corresponds to the normalized top of atmosphere (TOA) reflectance values of ETM+ bands 1, 2, 3, 4 and 5 (corresponding to Sentinel-2 bands 2, 3, 4, 8 and 11).
Training itself was performed by using libsvm[3] taking less than 20s on an Intel(R) Core(TM) Duo @2.80 GHz.

Results

Lausitz, Germany, 14.06.2001



RGB Composite

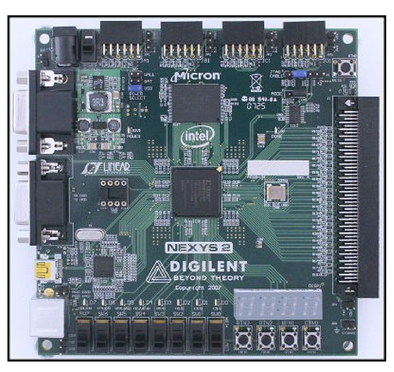


Cloudmask

An overall analysis using 276 ETM+ Scenes (altogether ~10 billion pixel) covering all seasons and regions yields a **median accuracy value of 98.0%** via the confusion matrix compared to the ACCA algorithm[4] used for Landsat 7 (95% confidence interval: [100%/57.2%])

Technical Realization

- Implementation of the algorithm on a Nexys2 with one SDRAM module and a clock rate of 12.5 MHz
  $\Rightarrow$ one pixel takes 5 clock cycles, i.e. $4{*}10^{-7}$s.
- Limiting factor: RAM access
- Theroetical speed: 1 pixel per clock cycle

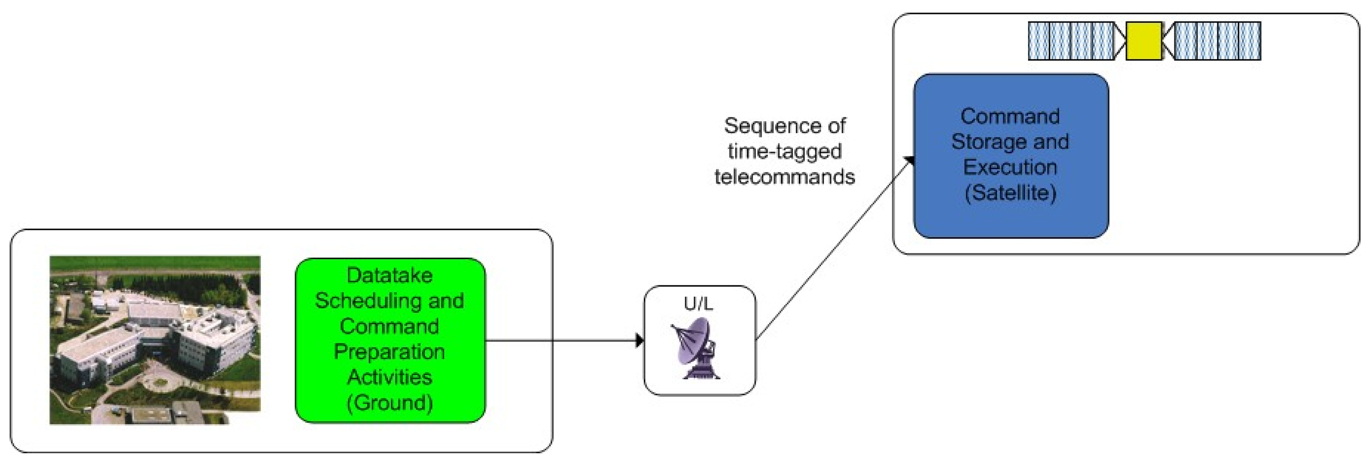


Future Work

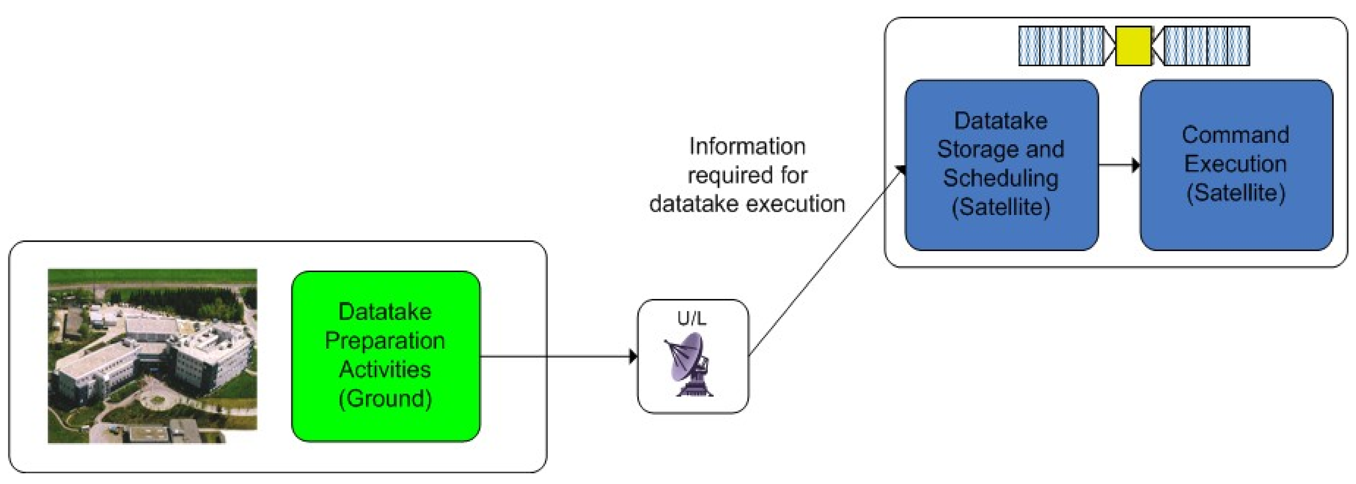
- Analysis of the performance of different kernels for the SVM
- Examination of a different dataset (MODIS)
- Creation of training datasets for different seasons and latitudes

On-Board Planning

Information flow when using on-ground scheduling



Information flow when using on-board scheduling



Pros and Cons

Both the on-board scheduling and the on-ground scheduling solution have advantages and disadvantages.
The biggest advantage of the on-board solution is the possibility of an immediate reaction to the current state of the satellite during payload operations. This can increase the amount of useful payload data returned by the satellite. Furthermore the scheduling process on ground is not necessary if everything works as expected on-board. This can potentially reduce operations effort in the ground control center, as manual labor is reduced.
Interactive on-board scheduling has also some disadvantages with the most important one being the loss of control about some satellite activities by the control center. Execution of datatakes and commanding is at least partly done on-board driven by unforeseeable boundary conditions. During each ground station contact the satellite will be found in a not exactly anticipated state by ground. If life-limited items are used during payload operations, a tracking of the operations time is only possible after datatake execution. A further drawback is the additional effort for software development and qualification for the satellite. Furthermore safety mechanisms must be developed and tested to assure that on-board commanding do not harm the satellite in any way.

Conclusion: The overall driver for the use of on-board scheduling will be the additional return of payload data - either used by the scientific community or as a commercial return during selling of data. If the value of additional data exceeds the implementation effort significantly, this technology will be used increasingly in future satellite missions.

[1] Schwenk K. and Goetz K., "Real-Time Evaluation of Remote Sensing Data on Board of Satellites," fpl, pp.399-400, 2011 21st International Conference on Field Programmable Logic and Applications, 2011
[2] Christianini N. and Shawe-Taylor J. (2006), An Introduction to Support Vector Machines, United Kingdom, Cambridge University Press
[3] Chang, C. and Lin, C. (2011), LIBSV: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology. 2(3): 27:1-27:27
[4] Irish, R, Barker, J., Goward, S. and Arvidson, T. (2006), Characterization of the Landsat-7 ETM+ Automated Cloud-Cover Assessment (ACCA) Algorithm. Photogrammetric Engineering & Remote Sensing, 72(10): 1179-1188