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DYNAMIC TARGETING SCENARIO TO STUDY THE PLANETARY BOUNDARY LAYER

Alberto Candela, Juan Delfa Victoria, Itai Zilberstein, Marcin Kurowski, Qing Yue, Steve Chien

Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Drive, Pasadena CA 91109, USA

ABSTRACT

Dynamic targeting (DT) is an emerging concept for improving science yield on Earth-observing missions limited by power-constrained sensors. DT uses a lookahead sensor together with on-board decision making to save resources for valuable observations in the future. Previous work has focused on developing DT mission use cases, such as storm hunting and cloud avoidance, that have relatively straightforward observation goals (i.e., look for storms, avoid clouds). However, DT has the potential to improve the science return of more complex missions and studies. To demonstrate this, we present and develop a new DT mission scenario to study the Planetary Boundary Layer (PBL). This paper describes the elements of our PBL mission scenario, which not only only involves multiple spacecraft, but also more sophisticated instruments, science models, and on-board decision making.

***Index Terms*—** New Observation Systems, Remote Sensing, Autonomous Earth Satellite, Planetary Boundary Layer, Artificial Intelligence

1. INTRODUCTION

Dynamic Targeting (DT) is an emerging concept in which a satellite uses data from a lookahead instrument so it can intelligently reconfigure and point a primary instrument that is power constrained (Fig. 1). The goal is to save energy for valuable observations that can be identified in advance with the lookahead sensor, thus improving science return on the mission. For example, in the Smart Ice Hunting Radar (SMICES) a forward-looking radiometer is used to detect and then selectively target rare convective ice storms using a power-hungry radar [1]. Several dynamic targeting algorithms have been developed for on-board decision making using ideas from operations research and artificial intelligence; these algorithms have been tested on different simulation studies that involve storm hunting and cloud avoidance applications [2, 3]. Tapia and Grogan expand the notion of DT for storm hunting to two spacecraft: a leading satellite and a trailing satellite [4]. Recent work matures the concept of DT by introducing more realistic instrument slewing models and physical constraints, and by incorporating machine learning to improve the on-board targeting algorithms [5].

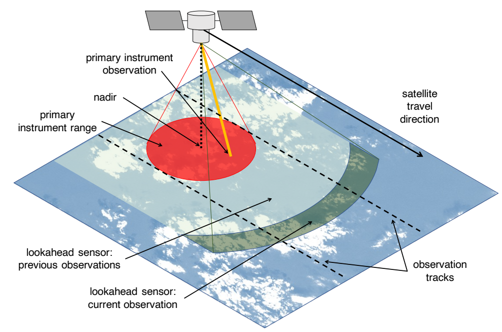

Fig. 1. Dynamic targeting is a concept that uses information on board from a lookahead sensor to identify future targets for a primary pointable instrument, thus improving science yield when subject to operational and power constraints.

This work presents and develops a new mission scenario in which DT is leveraged to better study the Planetary Boundary Layer (PBL). The PBL is the lowest part of the troposphere which is subject to direct Earth-atmosphere influence because of its proximity to the surface of the Earth. Several of the key PBL science questions are about the interactions between PBL thermodynamics and global processes that can only be properly observed from space [6]. A global PBL observing system is urgently needed to address fundamental PBL science questions and societal applications related to weather, climate and air quality. This is supported by the 2017 National Academies of Sciences, Engineering and Medicine Earth Science Decadal Survey, which recommended the implementation of a PBL incubation program [7]. Our previous DT mission scenarios focused on simpler atmospheric phenomena and their corresponding use cases (i.e., storm hunting and cloud avoidance [3]). By contrast, our new PBL scenario requires more sophisticated instruments, science models, and on-board objectives, as well as multiple spacecraft. The rest of the paper describes these elements in greater detail.

Contact author: Alberto Candela (alberto.candela.garza@jpl.nasa.gov)
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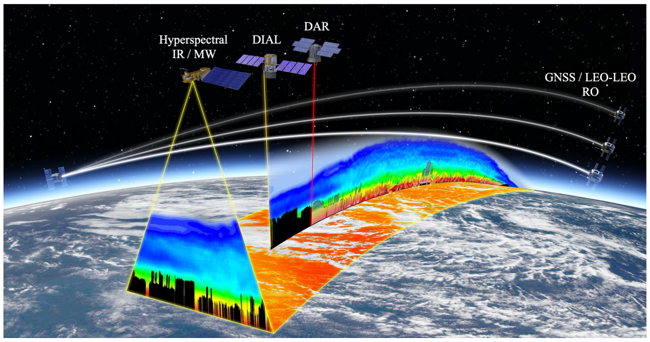


Fig. 2. Mission concept to study the PBL by Teixeria et al. [6]. The concepts consists of three satellites: one lookahead satellite that carries hyperspectral sounders (infrared and microwave) to use as a source of contextual information, and then two primary satellites that collect vertical profiles of the PBL, each using a unique differential absorption instrument.

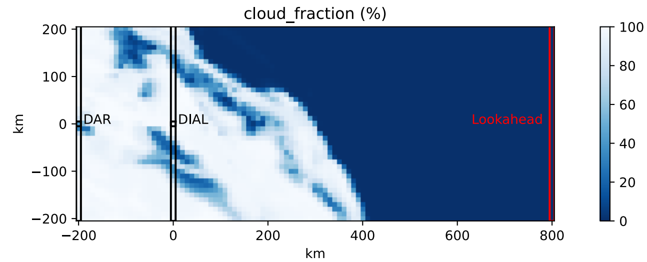


Fig. 3. Three-spacecraft simulation.

2. MISSION SCENARIO

In this work, we employ a modified version of the mission concept that was originally proposed in the study report by Teixeira et al. for a PBL observing system [6]. This concept consists of a "train" of three low Earth orbit (LEO) spacecraft: one lookahead satellite followed by two primary satellites (Fig. 2 and Fig. 3).

The lookahead satellite carries two push-broom hyperspectral sounders, infrared and microwave, that offer a high spatial footprint with a horizontal resolution of 5-20 km. The instruments complement each other effectively: the infrared sounder provides observations at higher resolutions but is limited to clear skies or tenuous clouds, while the microwave sounder has a coarser resolution but can observe all types of skies, even cloudy ones. An analogous instrument is the Atmospheric Infrared Sounder (AIRS) [8] on NASA's Aqua satellite, which provides measurements of temperature and water vapor through the atmospheric column along with a host of trace gases, surface, and cloud properties. AIRS data is used by weather prediction centers around the world to improve their forecasts. In this work the idea is that the lookahead satellite: 1) measures various physical variables of interest for studying the PBL, such as water vapor, cloud properties, and temperature; and 2) use these variables to identify targets for the primary satellites on the mission.

One primary satellite carries a Differential Absorption Lidar (DIAL), while the other satellite has a Differential Absorption Radar (DAR) [9]. These are pointable sensors that provide higher spatial resolution and accurate vertical profiles. Both instruments have a whisk-broom scanning pattern with one degree of freedom (left-right pointing). The DIAL cannot see through clouds but it has a low power consumption (6 W). On the other hand, the DAR can penetrate clouds but it consumes much more power (200 W), hence it has a 0.25% duty cycle because it needs to be turned off most of the time.

In this mission concept the lookahead satellite detects targets of interest and generates observation schedules on-board for each of the primary satellites. This concept assumes that the lookahead satellite sends these schedules over using a small data rate through interlink communication.

3. SIMULATION STUDY

3.1. Simulation Framework

We adapted and improved our satellite simulation framework that was originally developed for DT for a single spacecraft [3]. The new framework simulates satellite orbits as well as instrument observations that would be collected by each of the three spacecraft (Fig. 3 and Fig. 4). General Mission Analysis Tool (GMAT) [10], an open-source space mission analysis tool, was used to simulate and generate realistic satellite trajectories. For each satellite, we simulated a LEO with a 65 degree inclination, a 800 km altitude, an approximate period of 100 minutes, and an eccentricity of 0 (Fig. 4). In our concept the lookahead satellite is 800 km ahead of the primary satellites (Fig. 3). Hence, on-board computation and interlink communication must not exceed 2 minutes. There is a distance of 200 km (about 30 seconds) between the DIAL and DAR satellites. DIAL should only be pointed at targets that are not obstructed by clouds.

3.2. Variables of Interest

The PBL can be classified and studied according to a number of parameters such as climate zone or surface type [11]. At the same time, a number of properties such as landform, daytime, and sky conditions can impact the PBL status and should be taken into consideration when studying the PBL [12]. Here we generally focus on three kinds of conditions that impact PBL types: static (surface), time (daytime, season), and dynamic (atmosphere). These conditions are listed in Table 1. We assume that dynamic variables are observed using the lookahead sensors (sounders), whereas static and time conditions are readily available on board the satellite.

Table 1. PBL properties defining observation values

Variable	Values
Static (Surface)	
climate zone	tropical, subtropical, polar
landform	land, ocean
Time	
daytime	day, night
season	Spring, Summer, Fall, Winter
Dynamic (Atmosphere)	
cloud fraction	%
water vapor	kg/m^2
air temperature	K

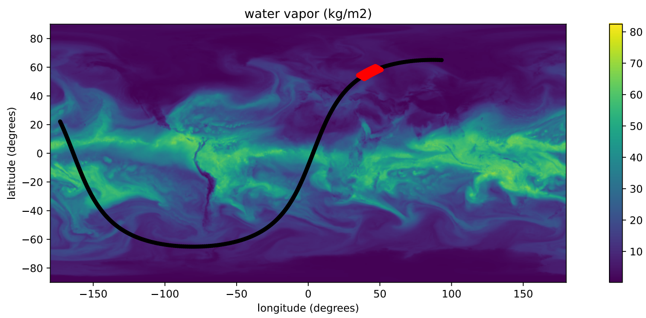


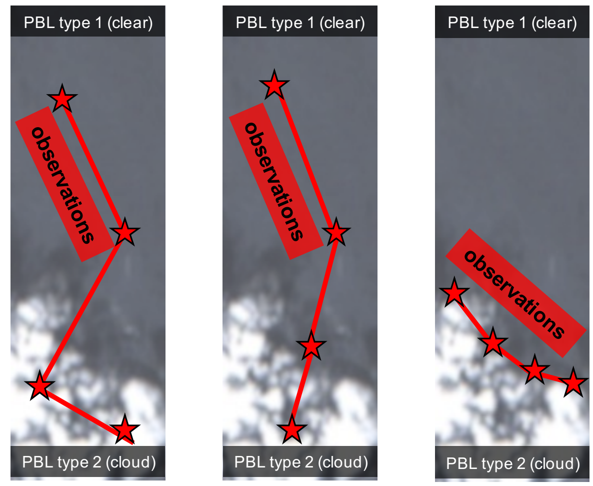
Fig. 4. The mission simulation framework uses the GEOS 5 Nature Run dataset to simulate instrument observations (red) that would be collected along a satellite trajectory (black).

3.3. Dataset

The framework simulates the aforementioned conditions (Table 1), especially dynamic ones (water vapor, clouds, temperature) using the GEOS-5 "Nature Run" dataset [13]. This is a global, 2-year computer simulation for the period June 2005 through May 2007. This model simulation is driven by prescribed sea-surface temperature and sea-ice, daily volcanic and biomass burning emissions, as well as high-resolution inventories of anthropogenic sources. The Nature Run dataset has a high horizontal resolution (7 km) and provides many standard meteorological parameters (e.g., wind, temperature, moisture, surface pressure, cloud conditions, etc.).

4. OBSERVATION STRATEGIES

A vital element of DT is on-board decision making. Previous work on DT focuses on simpler atmospheric phenomena and thus algorithms that favor *exploitation*. For example, storm hunting consists of prioritizing storm observations, and cloud avoidance prioritizes clear sky observations. By contrast, this new PBL scenario needs to be more comprehensive and also consider *exploration*, that is, observing different PBL types and conditions throughout the globe in a diverse and representative manner. To this end, we propose three different PBL observation strategies that offer different balance levels between exploration and exploitation (Fig. 5).



a) Diverse b) Representative c) High-gradient

Fig. 5. Three DT sampling strategies for studying the PBL.

4.1. Diverse Sampling

This strategy favors exploration over exploitation. It collects a balanced number of observations of different PBL types using established concepts from information theory [14] (Fig. 5 a). The notion of Shannon entropy H measures information in observed data. A small entropy means that our set of observations X is diverse, whereas a large entropy indicates the opposite. This results in the following maximization problem:

$$\max_X H(X), \quad H(X) = -\sum_{x \in X} P(x) \log(x). \tag{1}$$

4.2. Representative Sampling

This strategy balances exploration and exploitation. It gathers observations that better explain the variability of the whole scene by using theory and algorithms for near-optimal sensor placements [15] (Fig. 5 b). The goal here is to collect observations X that minimize the difference d (e.g., Euclidean distance) between a predictive function $\hat{f}_X$ that is constructed using X (e.g., machine learning), and the real underlying function f (i.e., the actual scene):

$$\min_X d(\hat{f}_X, f), \quad d(\hat{f}_X, f) = ||\hat{f}_X - f||_2 \tag{2}$$

4.3. High-Gradient Sampling

This strategy favors exploitation over exploration. It targets high-gradient locations, thus observing interesting phenomena on the boundaries between different PBL types (Fig. 5 c).

We propose to maximize a simple cumulative function F that is a linear combination of gradient magnitudes $||\nabla V_i(X)||$, one for each of the $i = 1, \dots, n$ variables V_i (e.g., water vapor, clouds, temperature, land vs. ocean, etc.). That is:

$$\max_X F\left(\nabla V_0(X), \dots, \nabla V_n(X)\right), \tag{3}$$

$$\text{where} \quad F(\dots) = \sum_{i=1}^{n} w_i ||\nabla V_i(X)||. \tag{4}$$

5. CONCLUSIONS AND FUTURE WORK

This work presents a DT mission scenario to study the PBL. The mission concept consists of a train of spacecraft: a lookahead satellite followed by two primary satellites (DIAL and DAR). Each satellite carries a different set of instruments with synergistic properties for the mission. This paper also describes our DT simulation framework that has been adapted to incorporate several spacecraft and multiple variables of interest for studying the PBL. Finally, this work proposes and formulates three different observation strategies as optimization problems that offer varying levels of balance between exploration and exploitation.

Future work will use state-of-the-art planning algorithms to solve the proposed optimization problems within feasible and realistic compute times for a mission of this nature. It will also conduct a thorough evaluation and comparison of the proposed observation strategies in a simulation study, analyzing the strengths and weaknesses of each.

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