Crop Optimization in Space with Machine learning & Offline computation of Strategies – COSMOS

Key words : Bioregenerative Life Support Systems (BLSS), Precision Agriculture, Robotics, Data Collection, Machine Learning (ML), Computer Vision (CV), Sequential Decision Making under Uncertainty, Reinforcement Learning (RL)

Department: Aerospace Vehicles Design and Control Department (DCAS)

JOB DESCRIPTION:

Advances in space exploration require human beings to be in space for the long term. Indeed, permanent settlement on other planets is now very much on the agenda, as are long space travels. However, supplying these missions from Earth would be too costly, if not impossible. A promising solution is to move towards closed-loop systems and bioregenerative life support systems (BLSS) [67, 6] to ensure and maximize recycling of resources, in particular water, oxygen and food.

The growth of plants is therefore a key aspect, that must be carried out while minimizing the use of resources which are limited therein [33, 64]. In addition, according to the latest report by the IPCC (AR6), climate change and resource depletion will also make life increasingly difficult on Earth. Conditions favourable to agriculture in particular will be rarer and more difficult to maintain. Solutions therefore need to be found to ensure the long-term preservation of mankind, both on Earth and in space. In future missions, astronauts will have limited time for crop cultivation, as their main focus will be on completing mission objectives. Therefore, upcoming space crop systems must be designed to require less crew involvement than current systems, incorporating more automation to streamline the process [52, 49, 47].

Monitoring the growth and health of plants throughout their life cycle is essential, not least to guarantee the safety of the food consumed by astronauts during these missions. Advanced imaging techniques can gather essential data enabling non-invasive and automated assessments of plant health that require minimal crew involvement. Swiftly identifying signs of nutrient deficiencies, drought or infections enables early response, which ultimately improves the success of long-term space missions. In this context, the thesis aims to develop Artificial Intelligence (AI) tools to ensure sustainable and resilient plant cultivation despite resource and environmental constraints. This challenge includes the optimization of plant cultivation systems, particularly in the extraction of useful information from their sensor measurements, as well as in the decision support and execution of these systems. It therefore focuses on AI for precision agriculture [59] in BLSS, with the overall objective of maximizing production, minimizing resource consumption, and more generally optimize the system according to appropriate criteria (e.g. Advanced Life Support System Evaluator, ALiSSE [9, 5]).

The thesis will delve into the two following interdependent challenges:

• Estimating the state of plants and their environment using machine learning (ML) and computer vision (CV) algorithms to make informed decisions based on the collected data,

• Computing sequential decisions using planning and reinforcement learning (RL) algorithms to compute effective and economical autonomous cultivation strategies over the long term.

With the help of robotics, this study aims to enrich AI methods for sustainable agriculture in unsuitable environments. It will pave the way for autonomous plant cultivation systems 2 capable of analyzing and even reacting to the cultivation process in order to rapidly obtain healthy plants while making optimum use of space and resources (nutrients, water, energy, etc).

Regarding AI, this thesis tackles three main theoretical challenges:

• The control of a plant growth system through the estimation of the plant state (e.g. leaf area) induces a partially observable (PO) framework (e.g. PO Markov Decision Processes [60]). This context poses the challenge of prior computation of estimators along with their conditional distributions. It also requires the development of optimization algorithms capable of handling the resulting complexity.

• Another challenge is the development of hybridization techniques between data-driven and model-based approaches to decision-making.

On the one hand, robot control requires the use of classical, model-based planning [26], so that the computation of a solution is possible despite the large number of states. On the other hand, the various possible behaviors of the plants are not available in advance, and its model must be learned through data collection with the plant growth system (e.g. Offline RL [35, 53]).

• The last challenge comes from the multi-criteria optimization: the objectives must be defined and aggregated appropriately to satisfy the requirements of the spatial context. For instance, the ALiSSE (Advanced Life Support System Evaluator) criteria, designed to assess the quality of life support systems [9, 5], includes the minimisation of total crew time (for system operation and maintenance), energy and material consumption, induced risk to humans, and maximisation of system reliability.

This thesis will result in publications in the AI fields of CV and sequential decision making under uncertainty, applied to robotics and space agriculture, as well as the creation of databases, algorithms and benchmarks that will be available online and useful for the study and development of autonomous plant growth systems for future space missions.

BACKGROUND:

Research into Bioregenerative Life Support Systems (BLSS) [67, 6] aims to enable the longterm settlement of human beings in environments where local conditions are not favourable. This is why ESA is interested in implementing BLSS: “For more than 30 years, the European Space Agency (i.e. ESA) is active in the field of regenerative life support systems. MELiSSA (Micro-Ecological Life Support System Alternative) is the European project of circular life support systems. It was established to gain knowledge on regenerative systems, aiming to the highest degree of autonomy and consequently to produce food, water and oxygen from mission wastes[1]”. As part of the MELiSSA project [32, 33], greenhouse design studies [51, 15, 72] and prototypes have been developed (e.g. for growing tuberous plants [46] in the ESA “Precursor of Food Production Unit” project), and a large amount of research work has been carried out (e.g. on hydroponic systems [44] and for growing potatoes in controlled environments [45]).

[1] https://www.melissafoundation.org/

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The CNES "SpaceShip FR" project, which began in 2019 in Toulouse, plans to build a lunar or Martian-type base to demonstrate solutions in various fields, such as health, energy, robotics, digital technology, plant cultivation and recycling. In terms of nutrition, the SpaceShip FR project plans to set up a hydroponic greenhouse, as well as a circular aquaponics system whose fish can be used to diversify the astronauts' daily diet and to create fertiliser from their wastes. Many experiments have already been carried out in space, one of the most recent being the production of chili peppers on the International Space Station by NASA three years ago: the first fruit to be grown in space and the longest experiment with plants. Indeed, NASA is also carrying out a great deal of research into systems for growing plants for food production [30].

Although a great deal of effort is being put into developing these plant cultivation systems for space, work on developing artificial intelligence methods to optimize their operation has only just begun in recent years, while models in this BLSS context have already been explored [50, 48]. On earth, on the contrary, numerous datasets (for example, [40, 54, 55, 73, 8, 16, 31, 69] for image segmentation, or [17, 36, 29, 43, 58] for disease detection), as well as models, simulation environments and algorithms [18, 61, 39, 68, 11, 24, 66, 25, 37, 42] have been produced by researchers.

Since 2019, around twenty Master's students have contributed to research into precision agriculture for BLSS during internships and research projects under the guidance of the supervisors of the proposed thesis. Progress on these projects was presented at MELiSSA conference (Nov. 22), at a webinar with the NASA KSC Space Crop Production team (Feb. 23), and at the UTIAS2 forum (Apr. 24). Test beds have been set up to collect data useful for the two main aims of the thesis, i.e. optimizing the perception capability and execution of these plant crop systems. One of these is a hydroponic system that can control light intensity and frequency, as well as nutrient concentration. Another test bed is a Farmbot, an open source agricultural robot. Both systems are equipped with sensors including a camera whose position can be controlled.

Although this project is looking at a new application for ISAE-SUPAERO, it concerns its fields of expertize, such as Artificial Intelligence (AI) – in particular Planning [13, 14, 23, 21, 34], Offline Reinforcement Learning [3, 1, 2], and Anomaly Detection [27] – as well as Advanced Space Concepts [7, 22, 12, 41, 28]. In particular, it will lead to greater expertise in the design of AI tools for systems containing living organisms, which is necessary for manned space missions. This thesis project proposes to develop tools for monitoring and controlling plant growth, similar to the tools developed by the supervisors for monitoring [20, 70, 71] and adapting [4, 56, 19, 10] the interaction of human operators with their systems.

WORK PLAN:

This thesis proposes to develop artificial intelligence tools to tackle two aspects of the problem of precision farming in life support systems: the optimisation of/

• the perception capabilities of plant cultivation systems, which involves using machine learning algorithms to extract useful information from the measurements of the sensors present in these systems. Typically, classification, object detection and image segmentation algorithms can be trained and used on the outputs of cameras present in plant growing systems, in order to estimate their state (size, weight, shape, orientation, health, leaf area, location, etc.).

• the execution of plant cultivation systems, which consists of taking advantage of planning [26] and reinforcement learning [62] to compute sequential decisions for the system. The aim is to develop planning and simulation models, in order to obtain better growing strategies.

The thesis will be carried out in the following stages:

• The first year of this thesis will focus on perception, with a literature review and benchmarks of computer vision methods for estimating plant state (e.g. classification, segmentation, etc.) The study of existing plant cultivation systems, and those available at ISAE-SUPAERO (hydroponic system and farmbot), will enable expert cultivation strategies to be defined and deployed in order to carry out initial data collection campaign and strategy evaluation.

• The second year will focus on sequential decision making: following a study of suitable control methods, models (e.g. based on PDDL [38] or RDDL [57]) and simulators (e.g. using Gymnasium [63, 65]) of plant cropping systems will be proposed, and benchmarks will be initiated, including resolution methods from the literature as well as new approaches. Strategies derived from these benchmarks and previously collected data, will then be deployed for a second data collection campaign and evaluation of these optimized strategies.

• Finally, the third year will see the completion of the benchmarks, the computation of new strategies with the newly developed algorithms and the latest data collected, and finally their deployment on available plant cultivation systems for evaluation.
This thesis, which aims to optimise the system's perception and decision-making capabilities, will lead to the publication of research work in the fields of learning for planning, in the context of partial observability, multi-criteria optimization, using both data-driven and model-based approaches to decision-making.

REQUIRED PROFILE:
The candidate must have a Master's degree (or equivalent) in Artificial Intelligence, Machine Learning, Computer Science, Mathematics, Computer Vision or Robotics. Specifically, she/he must have: - Advanced knowledge of Machine Learning/Deep Learning; - Advanced programming experience with Python and Machine Learning libraries; - Knowledge of Planning and Reinforcement Learning; - Good communication and writing skills in English; Ability to work independently.

START DATE: from October 2025.

LOCATION:
ISAE-SUPAERO, Toulouse, France.

RESPONSIBLE OF THE SUBJECT:

Nicolas DROUGARD – ISAE-SUPAERO (DCAS)
Thibault GATEAU – ISAE-SUPAERO (DCAS)

APPLICATION PROCESS:

All applications should be send by March 7th, 2025 at the last, with :

- resume,
- motivation letter,
- transcripts of master's degree.

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