ROBFORISK, Robot assistance for characterizing entomological risk in forests under climate constraints

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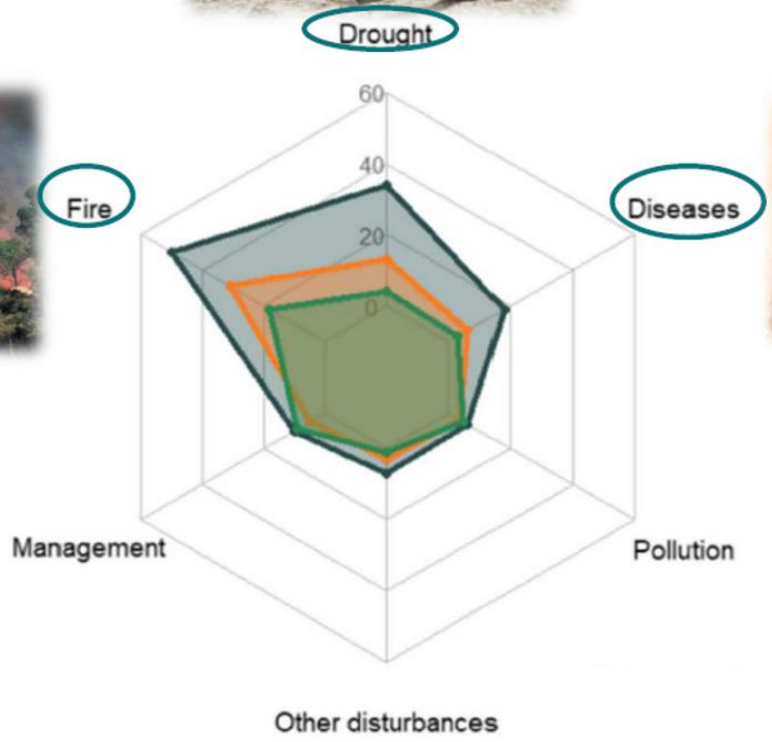
Forests, insects and climate change

Disturbances likely interact

Drought

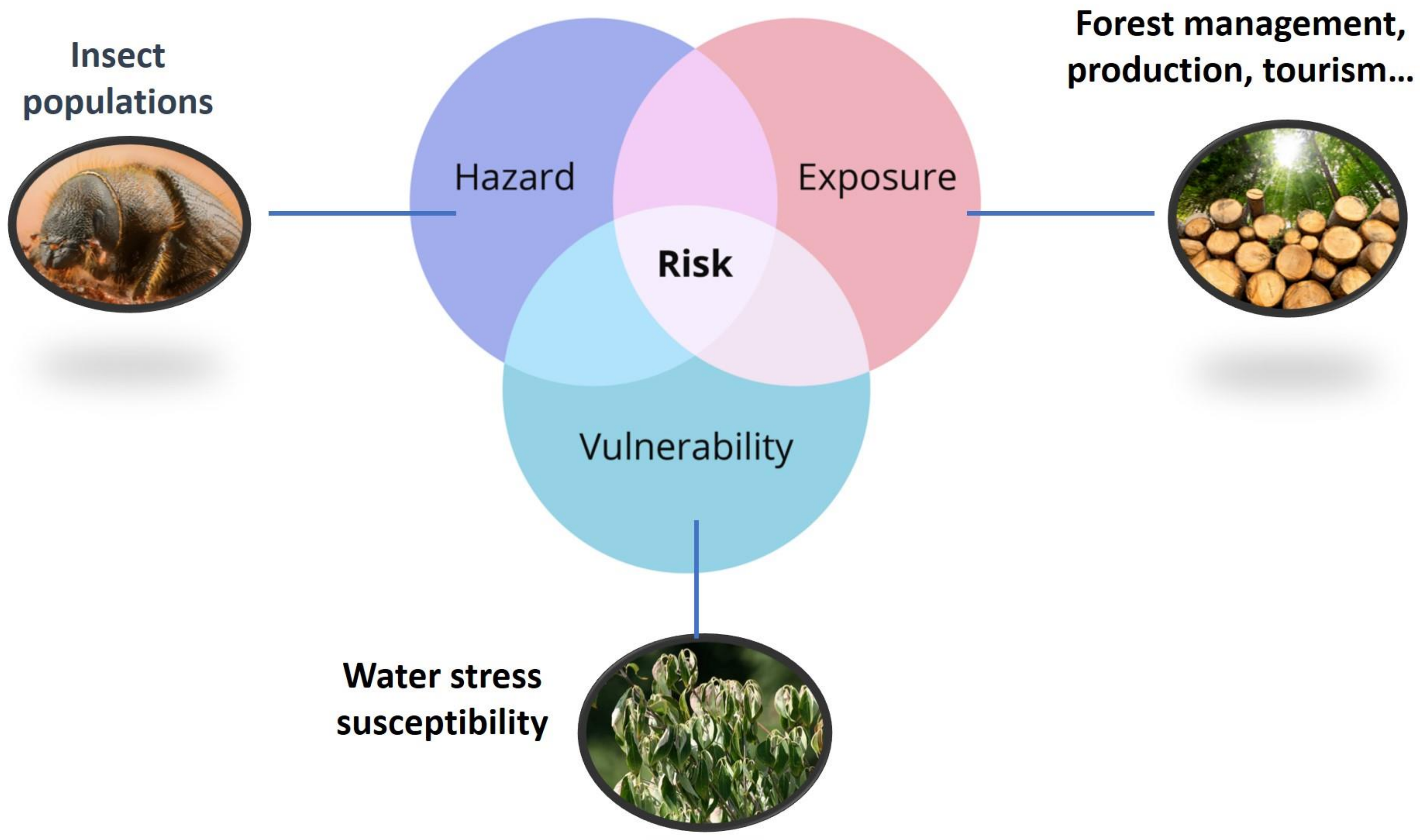
Fire

Insects
Pathogens



What is entomological risk in forests?

RISK = Hazard x Vulnerability x Exposure

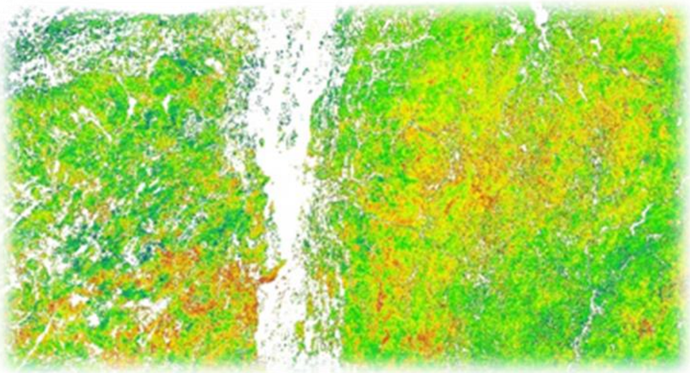


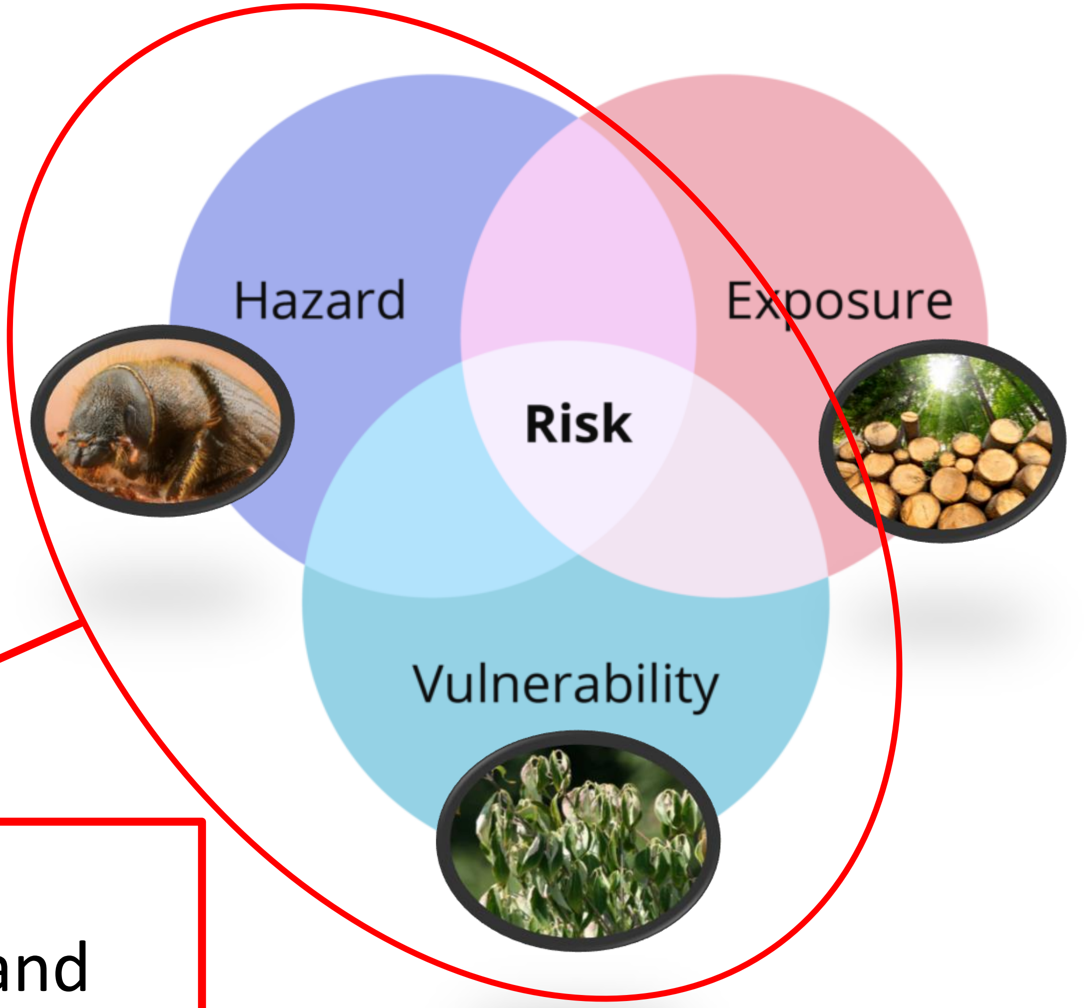
Characterizing entomological risk in forests

- Visual observations, remote sensing
- Most of the damage already occurred

= a constraint on forecasting entomological risk

Characterizing entomological risk in forests





Expected progress
= early indicators of tree responses to biotic and abiotic stressors (individual and population scales)

Characterizing entomological risk in forests

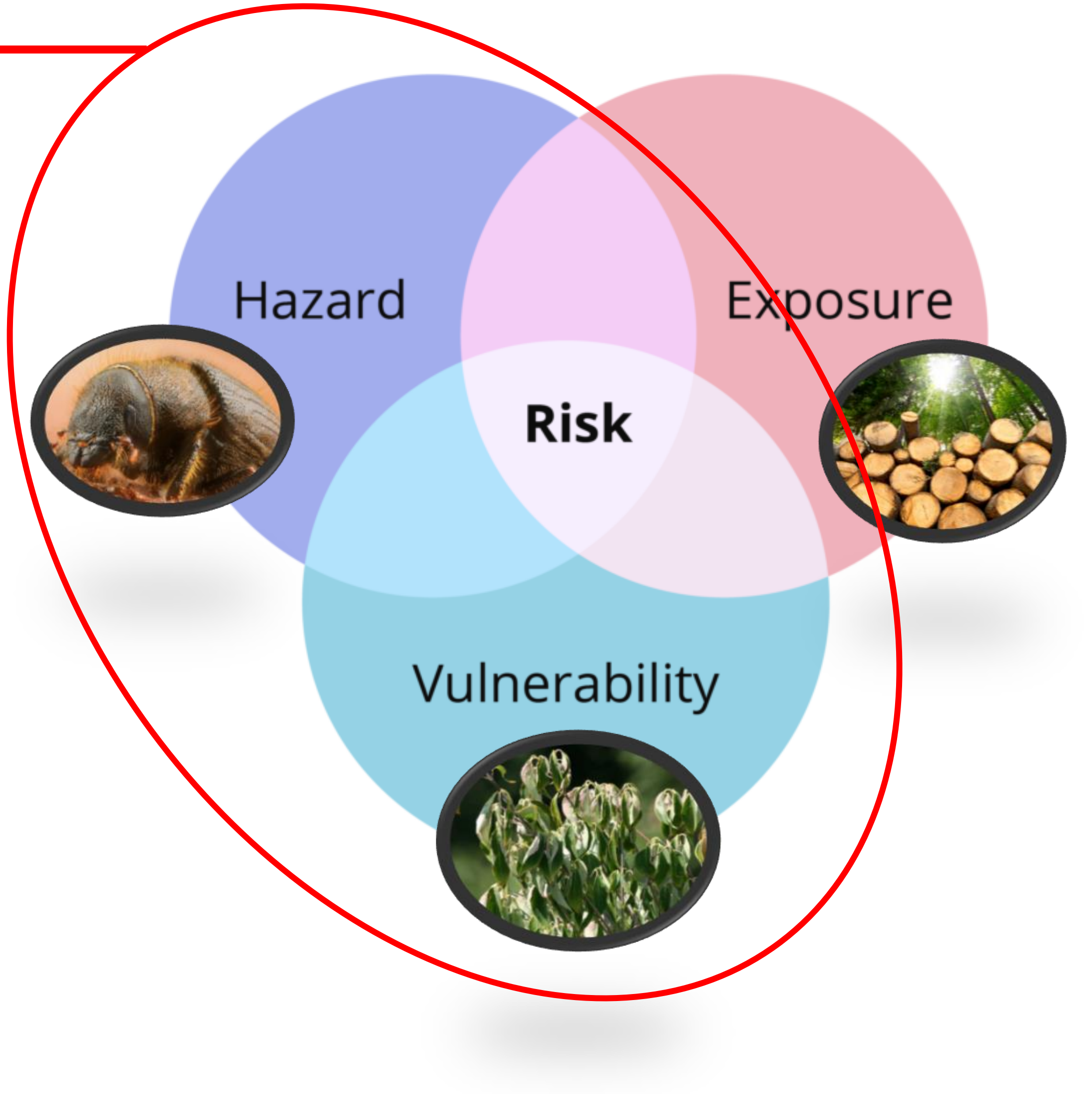
ROBFORISK

1. Improved knowledge of pre-determinants of insect hazard and tree vulnerability

➔ ***new indicators (multispectral imagery & chemistry)***

2. Novel technology for in situ spatial and temporal measurements

➔ ***On-board sensors for drones***

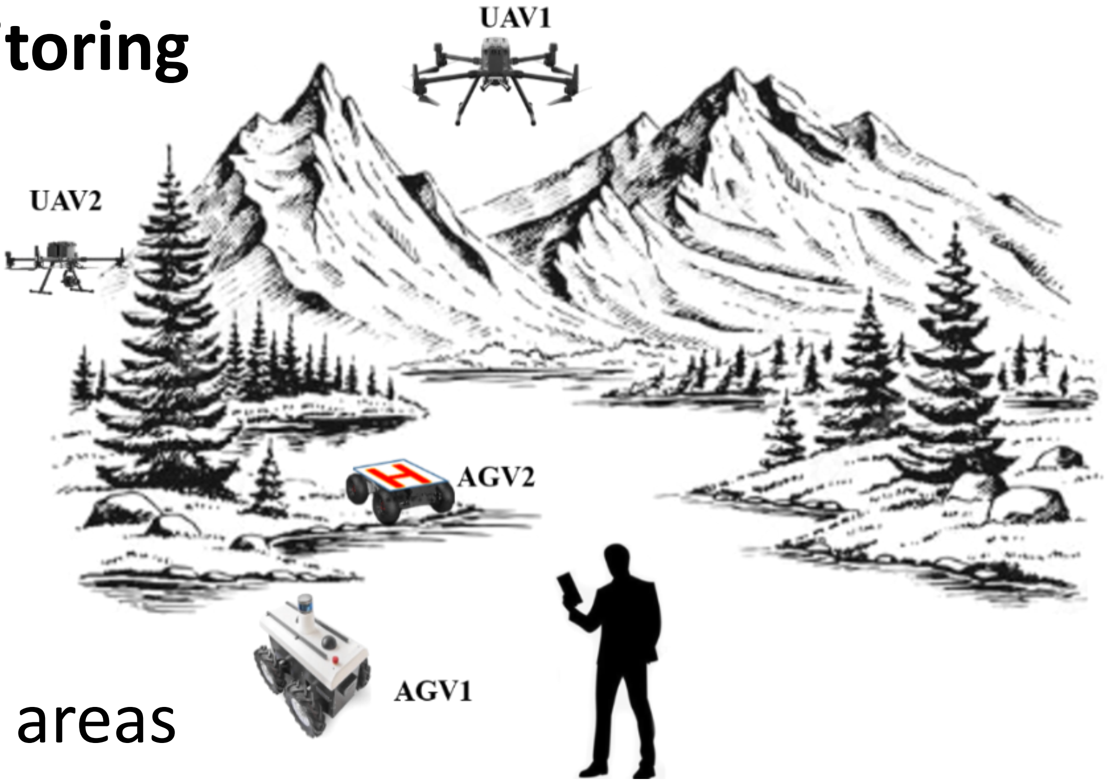


The ROBFORISK objectives

Robot assistance for forest health monitoring

- Targeted information collection
- High spatial resolution
- Time optimization

➔ lower monitoring costs across larger areas



Scientific challenges

Increasingly developing in agricultural crops, a gap of knowledge in forests

CHALLENGE #1

Functional links between multispectral/chemical characteristics and tree response to stress?

Can we measure them?

Scientific challenges

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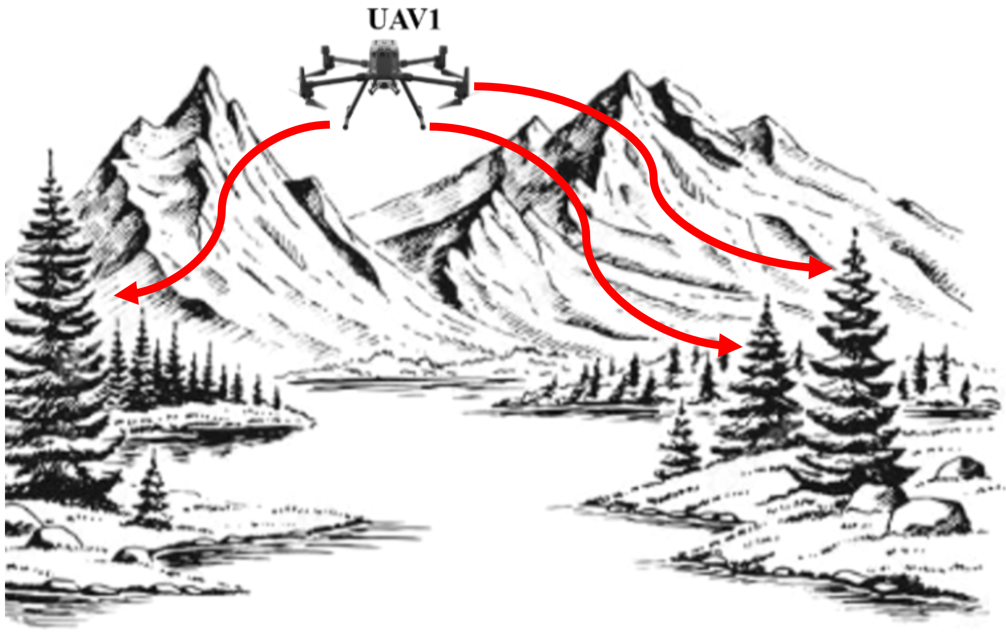
CHALLENGE #1

Functional links between multispectral/chemical characteristics and tree response to stress?

Can we measure them?

CHALLENGE #2

Automated positioning tasks using information from a multispectral camera is <u>groundbreaking</u>



Model system

Silver fir (*Abies alba*) dieback in Région Sud (France)

- Dieback dynamics since 2017
- Concomitant drought episodes and forest insect outbreaks: *Epinotia subsequana* (Lepidoptera)
- Individual and stand scales of damage
- Regional expansion

Epinotia subsequana

Mont Lachens (83; 1300-1600m asl) in 2017

Research axes & INRAE - Inria complementarity

1. Functional links between water stress,

***Epinotia* attacks and Silver fir physiology**

Experiment in progress (March-July 2023)
under controlled conditions:

Watered trees, water-stressed trees

➔ No insects, Insects attacks

Effects of drought, of insects, and of [drought x insects]

Insect performance, leaf metabolomics

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2. Measures of tree response to stressors with a multispectral camera

- From the controlled experiment (July 2023)
- To field conditions on stressed and non-stressed trees (Sept-Nov 2023)

SHARED INRAE-Inria engineer (2 years)

- Multispectral camera
- Detection and annotation algorithms for critical captured informations

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3. Robotics using multispectral camera and UAVs

Multispectral data

Visual servoing

3D reconstruction Géoréférencement

Takeoff/Landing/recharging Autonomously

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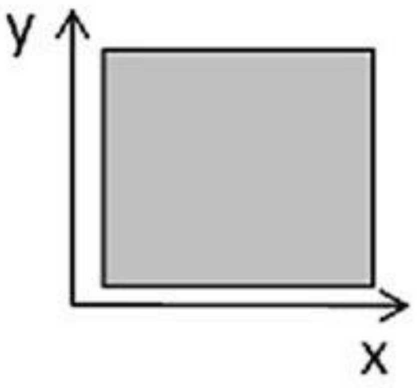
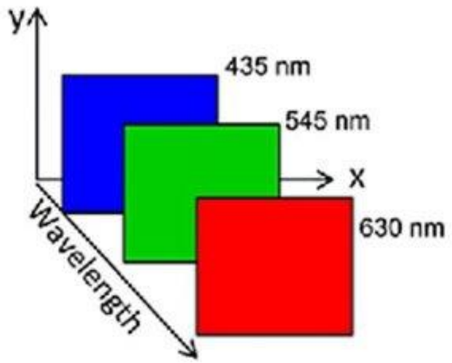
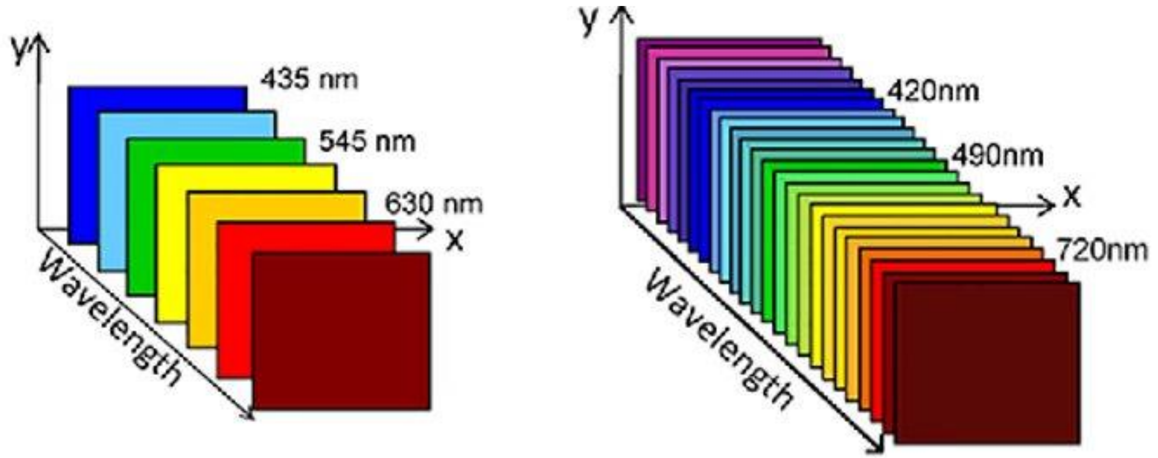
Overview – Camera's spectrum



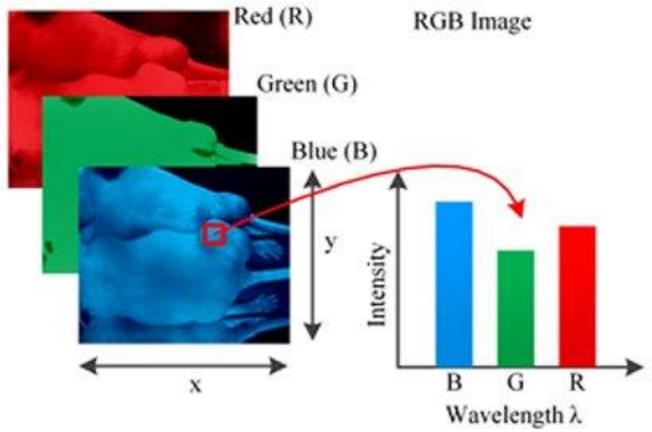
Monochrome spectrum



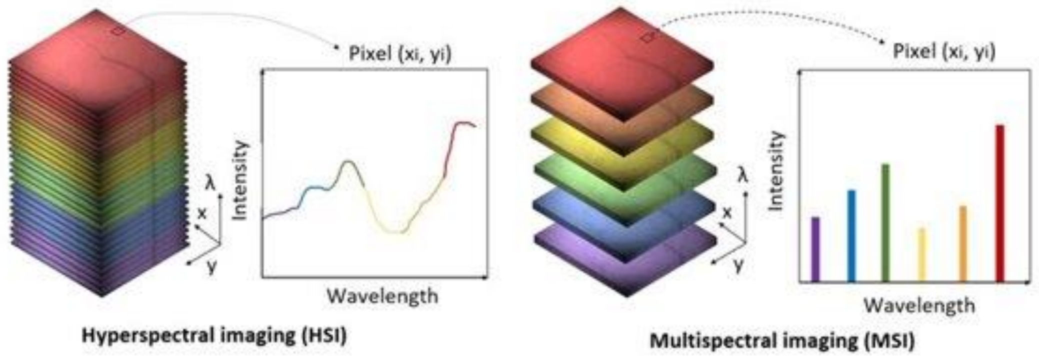
RGB spectrum



Multispectral and Hyperspectral spectrum



RGB Image



Multispectral/Hyperspectral Image

[1] - Ozdemir, Akin & Polat, Kemal. (2020). Deep Learning Applications for Hyperspectral Imaging: A Systematic Review. Journal of the Institute of Electronics and Computer.

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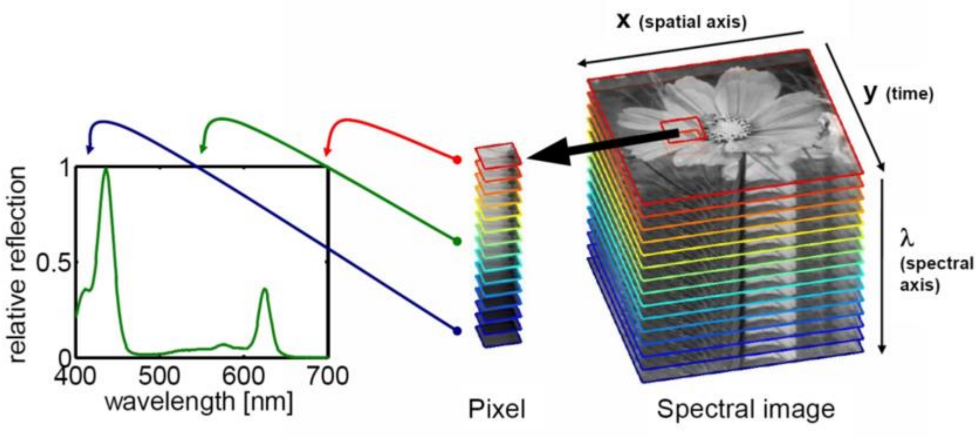
Importance of dimensionality reduction

Objective:

- Hyperspectral camera in conjunction with Visual Servoing

- **Efficiency**
  - It is computationally demanding and time consuming;
- **Redundant data**
  - Due to the high spectral resolution;
- **Noise reduction**
  - It often contains sensors noise and other effects;



Hyperspectral cube

[2] - Polder, Gerrit & Pekkeriet, Erik & Snikkers, Marco. (2013). A Spectral Imaging System for Detection of Botrytis in Greenhouses.

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Band Selection

- **Selects set of bands**
  - It preserves the spectral meaning of the channels
- **Noise reduction and Data-Compression**
  - Reduction of redundancy, it improves signal-to-noise ratio
- **Interpretability and Visualization**
  - Reduction of redundancy improve the interpretability of the spectral information
- **Two different methods**
  - Supervised and unsupervised methods

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Importance of dimensionality reduction

The aim is to find a representation matrix with the lowest rank that can be used as basis to construct the data.

observations

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n]$$

$$\mathbf{X} = \mathbf{DZ}$$

$$\boldsymbol{D} = \boldsymbol{X}_{\tilde{i}} = [\boldsymbol{x}_1, \ldots, \boldsymbol{x}_{i-1}, \boldsymbol{x}_{i+1}, \ldots, \boldsymbol{x}_n]$$

dictionary

Z coefficient matrix

$$\arg\min_{\mathbf{Z}} \ \operatorname{rank}(\mathbf{Z}) \quad \text{s.t. } \mathbf{X} = \mathbf{DZ}.$$

trace norm

$$\arg\min_{\mathbf{Z},\mathbf{E},\mathbf{J}} \ \|\mathbf{J}\|_* + \lambda\|\mathbf{E}\|_{2,1} \quad \text{s.t. } \mathbf{X} = \mathbf{DZ} + \mathbf{E}, \quad \mathbf{Z} = \mathbf{J}.$$

Noise

Problem solved using the *augmented Lagrange multiplier*:

$$\mathcal{L}(\mathbf{Z}, \mathbf{E}, \mathbf{J}, \mathbf{\Lambda}, \mathbf{\Gamma}) = \|\mathbf{J}\|_* + \lambda\|\mathbf{E}\|_{2,1} + \frac{\mu}{2}\left(\|\mathbf{X} - \mathbf{DZ} - \mathbf{E}\|_F^2 + \|\mathbf{Z} - \mathbf{J}\|_F^2\right) + \langle \mathbf{\Lambda}, (\mathbf{X} - \mathbf{DZ} - \mathbf{E})\rangle + \langle \mathbf{\Gamma}, (\mathbf{Z} - \mathbf{J})\rangle$$

Weight of the bands

affinity matrix

$$\mathbf{W}_i = \frac{\sum_{\mathbf{x}_j \in \mathbf{C}} \mathbf{E}_i}{RE_j} \sum_{\mathbf{x}_j \in \mathbf{C}, j \neq i} \mathbf{A}_{ij}$$

Number of bands

[3] - G. Zhu, Y. Huang, S. Li, J. Tang and D. Liang, "Hyperspectral Band Selection via Rank Minimization," in *IEEE Geoscience and Remote Sensing Letters*, vol. 14, no. 12, pp. 2320-2324, 2017.

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Multi-Robot System

The robots have to collaborate to collect data and map the environment.

It is challenging due to the complexity of the environment.

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Scientific issues

Constraints:

- One of the drones will be manually controlled by an operator;
- GNSS denied environment;
- Communication denied environment;
- Important to have precise localization of the robot;
- Need to geo-reference the scanned trees on the forest map;

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Acquisitions steps

1. Snapshots in the forest;

2. From the model we extract the bands useful to detect the illness;

3. We use the Visual Servoing approach with the drone in the forest, using the selected bands to get new complementary data;

4. Every 3 months, we extract a new model of the illness, and we update the useful bands;

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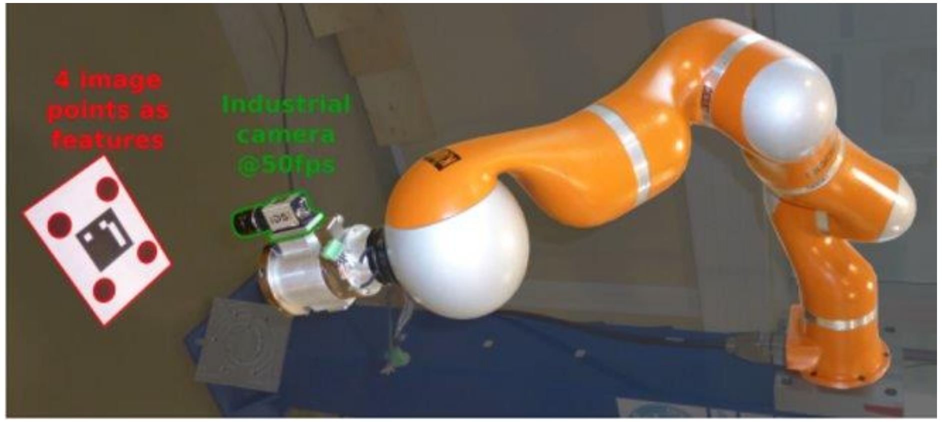
Visual Servoing



Kuka arm used for Visual Servoing

Direct Visual Servoing using a camera mounted in a mobile robot

[6] - Fusco, Franco, Olivier Kermorgant, and Philippe Martinet. "Integrating features acceleration in visual predictive control." *IEEE Robotics and Automation Letters* 5.4 (2020): 5197-5204.
[7] - G. Silveira and E. Malis, Direct Visual Servoing: Vision-Based Estimation and Control Using Only Nonmetric Information, *IEEE Transactions on Robotics*, 28 (4), pp.974-980, 2012.

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Visual Servoing – Hyperspectral camera

No research in the state-of-the-art using VS and Hypespectral camera

Similar existing works:

- Visual Servoing based on the colors of the image;
- Frequency based Visual Servoing;

[8] - C. Collewet and E. Marchand, "Colorimetry-based visual servoing," *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, MO, USA, 2009, pp. 5438-5443.
[9] - G. Silveira and E. Malis, "Visual servoing from robust direct color image registration," *IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, MO, USA, 2009, pp. 5450-5455.
[10] - E. Marchand, "Direct Visual Servoing in the Frequency Domain," in *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 620-627, 2020.

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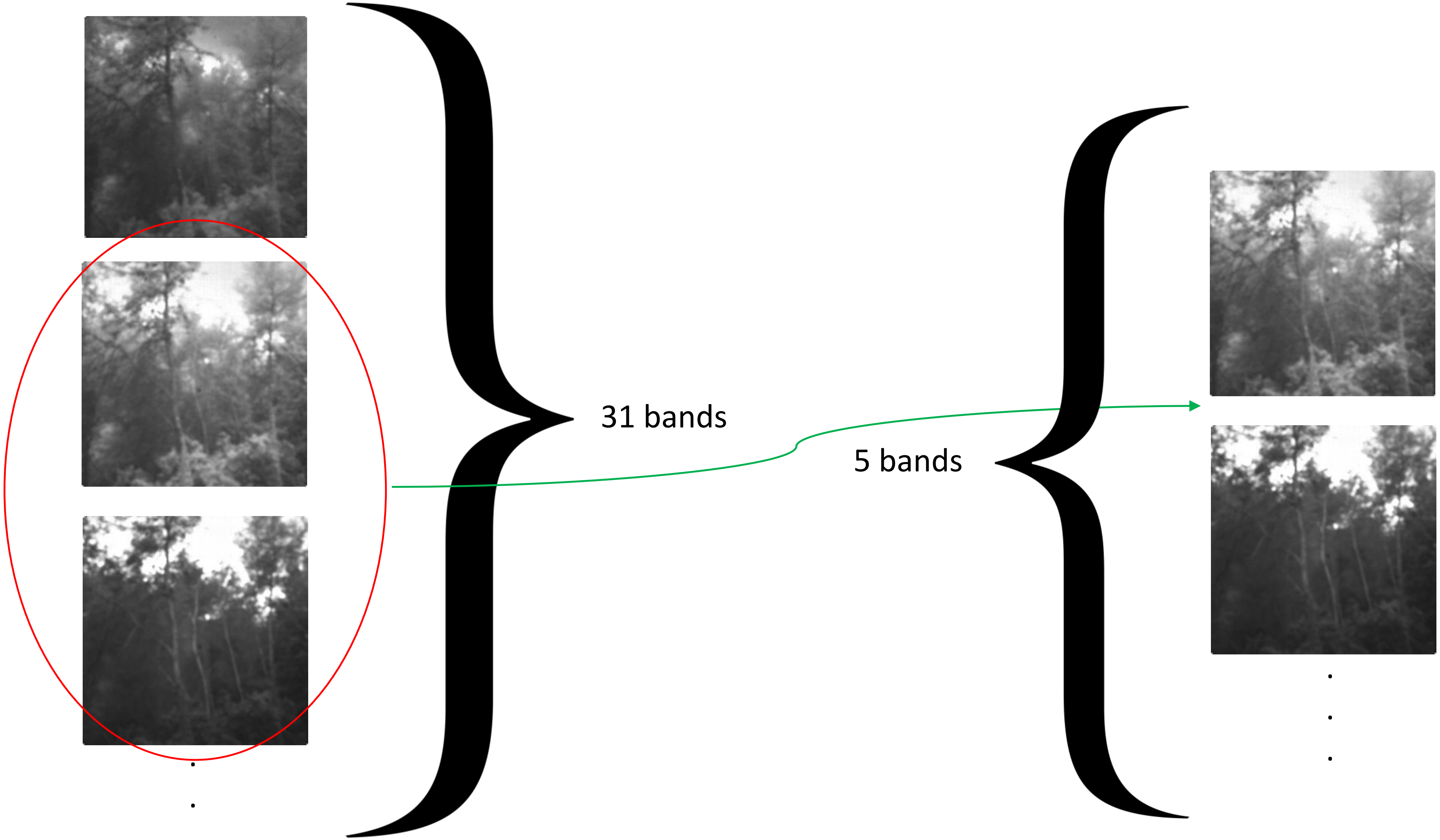
State-of-the-art band selection



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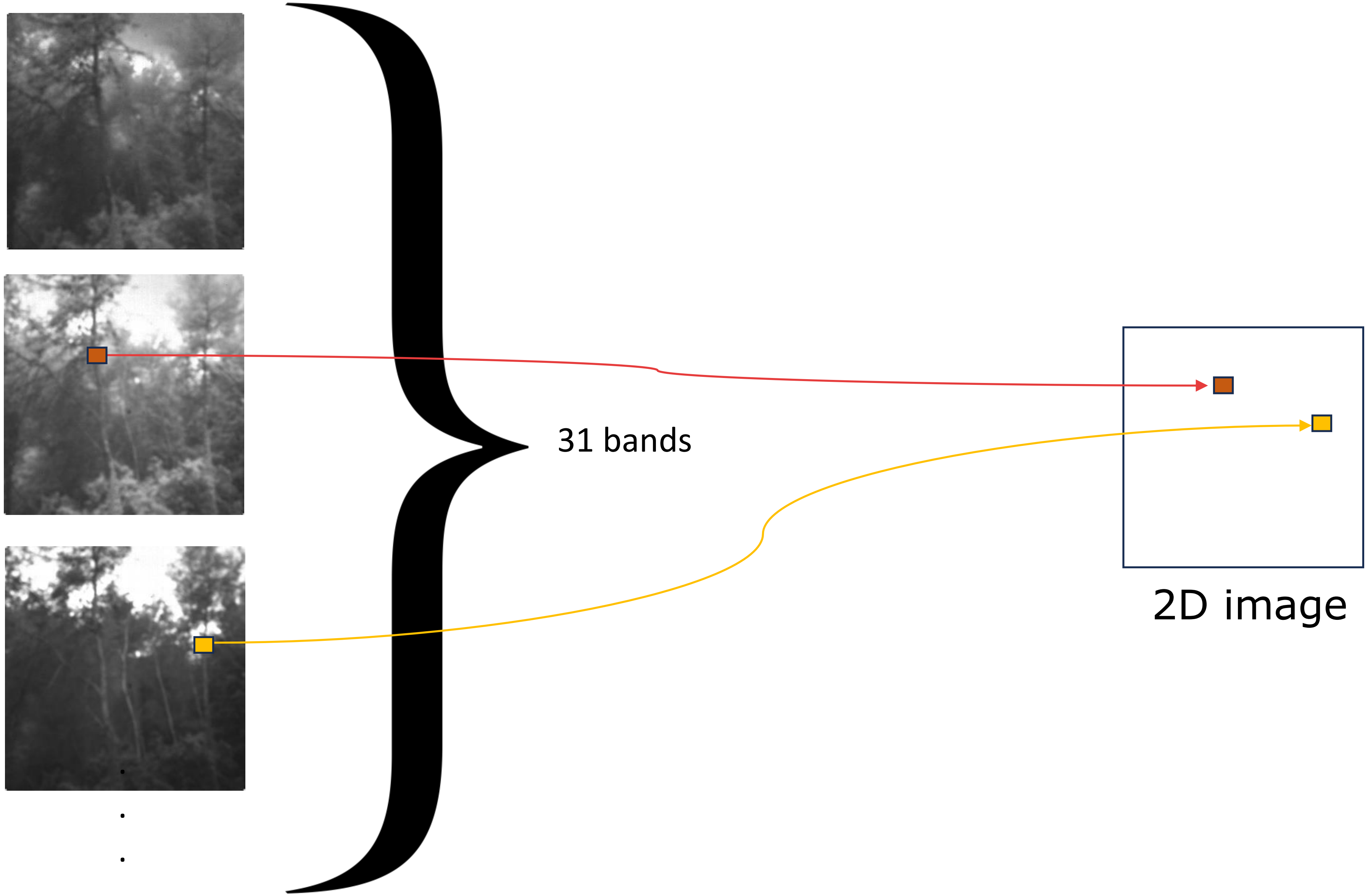
Novel approach



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Novel approach

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New 2D image

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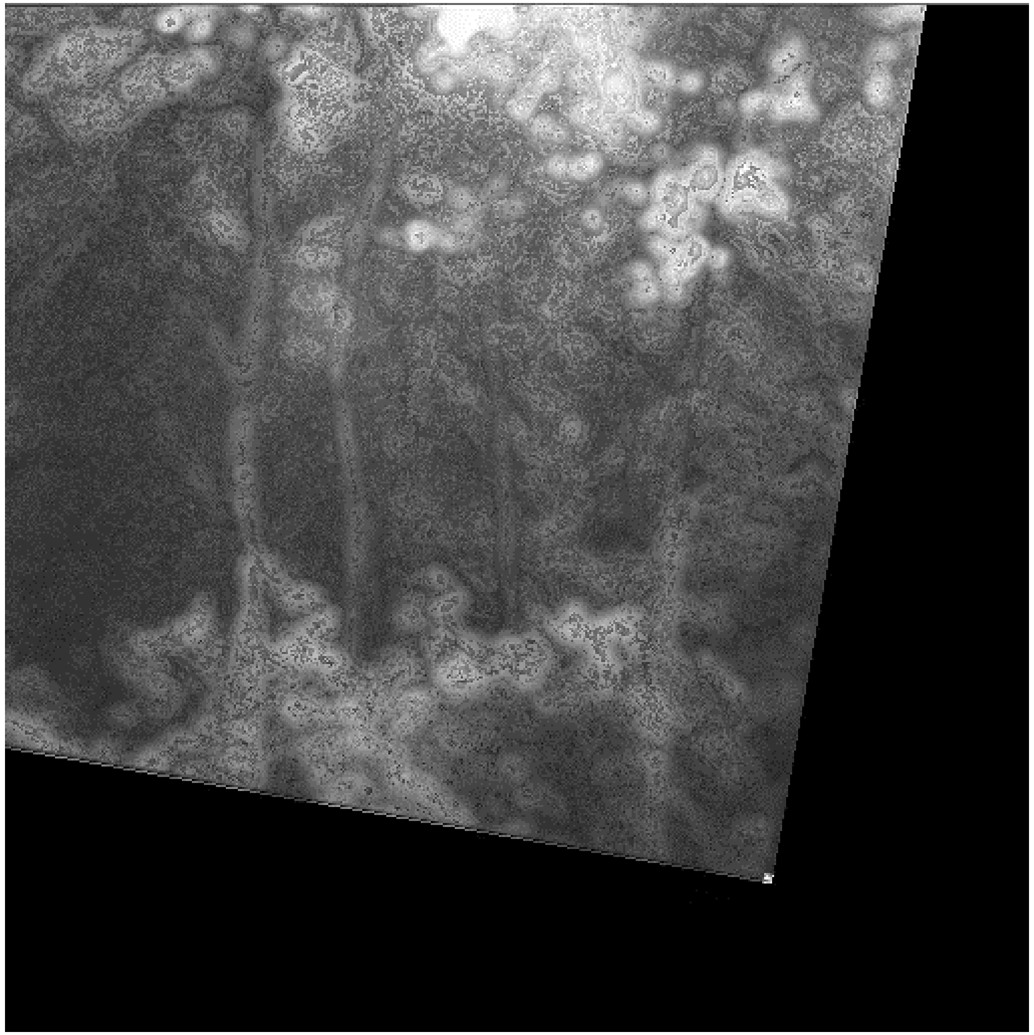
Simulation

Reference Image



Control error used:

$$\boldsymbol{\varepsilon} = \begin{bmatrix} \boldsymbol{\varepsilon}_{\upsilon} \\ \boldsymbol{\varepsilon}_{\omega} \end{bmatrix} = \begin{bmatrix} (\mathbf{H} - \mathbf{I})\,\mathbf{m}^{*\prime} + \rho^{*}\mathbf{e}^{\prime} \\ \vartheta\,\boldsymbol{\mu} \end{bmatrix}$$

[9] - G. Silveira and E. Malis, "Visual servoing from robust direct color image registration," *IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, MO, USA, 2009, pp. 5450-5455.

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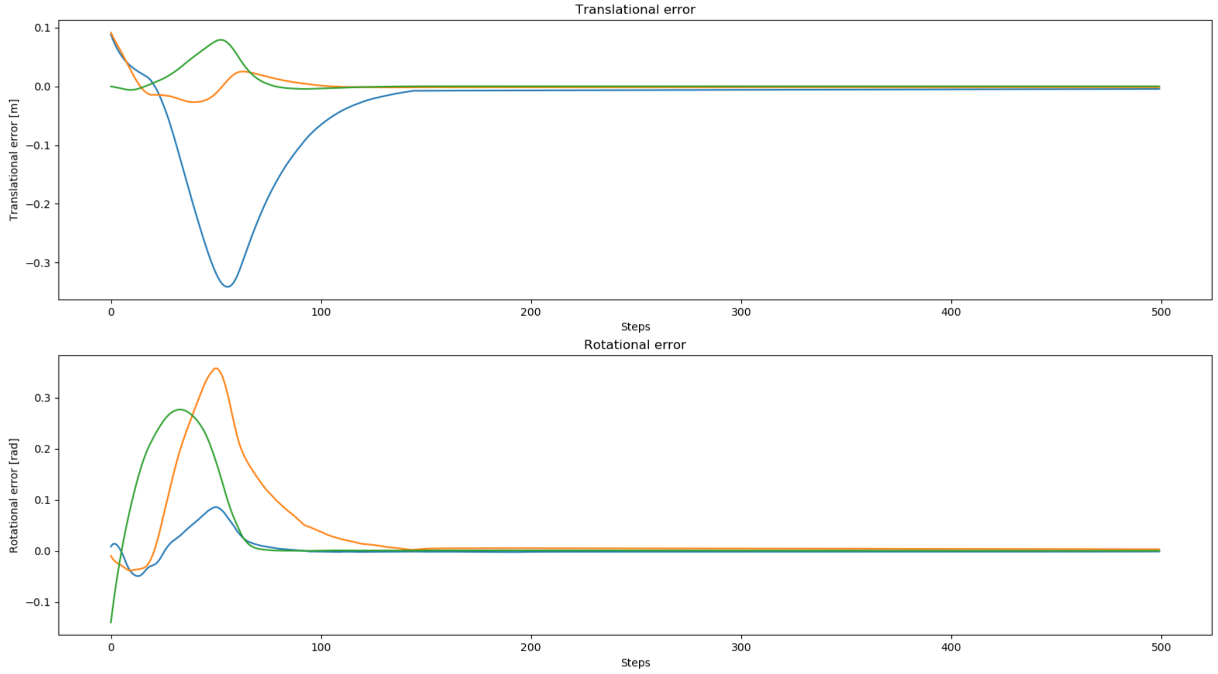
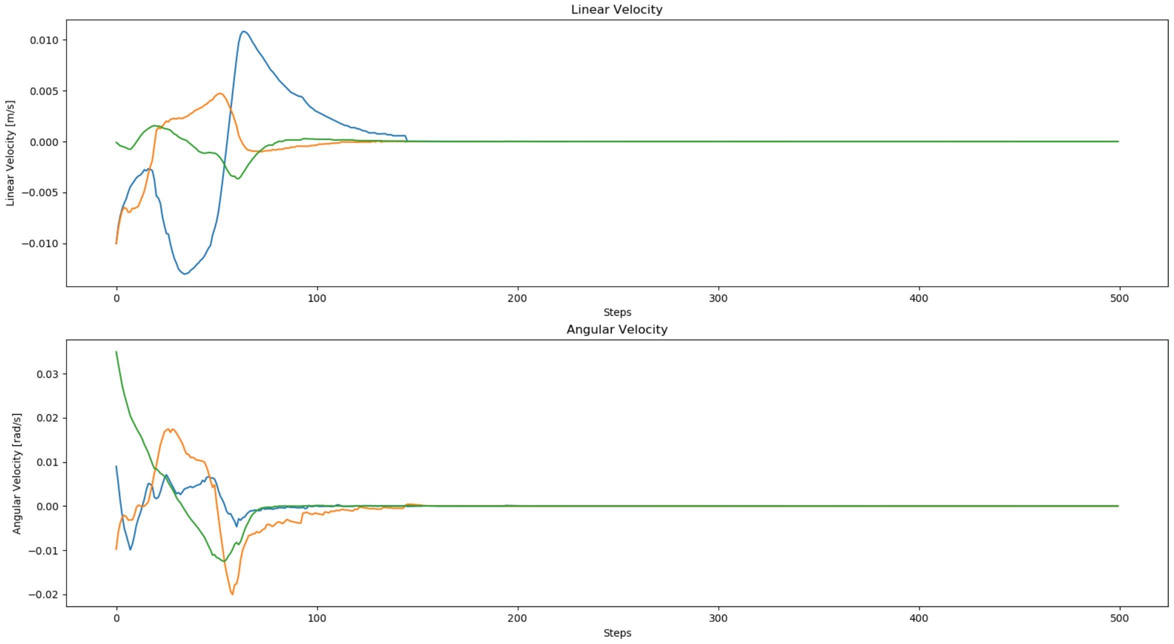
Results

Translational and rotational error



Linear and angular velocities



The ROBFORISK expectations

- INNOVATIVE APPROACH TO INSECT HAZARD AND TREE VULNERABILITY IN FORESTS

- TACKLE THE CHALLENGE OF DRONE VISUAL SERVOING USING MULTISPECTRAL CAMERA INFORMATION IN NATURAL ENVIRONMENTS

- INNOVATIVE RESEARCH ON PRE-SYMPTOMATIC STRESS TESTS OF INTEREST TO FOREST MANAGERS AND STAKEHOLDERS