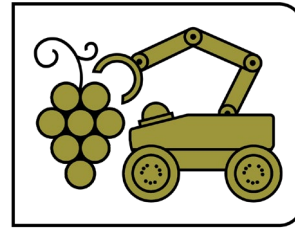


“Technology in Practice”

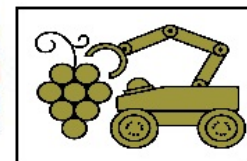
Thursday 29.10.2020, Friday 30.10.2020, Saturday 31.10.2020



POGHAR

Personalized Optimal Grape Harvest by Autonomous Robot

HUman-MACHines INteraction Laboratory (HUMAIN-Lab)
Department of Computer Science
International Hellenic University, Kavala, Greece



POGHAR

Co-financed by Greece and the European Union

The consortium

- ❑ Research organizations of IHU
 - ❑ Department of Computer Science (Kavala) – HUMAIN-Lab
 - ❑ Department of Agricultural Biotechnology and Oenology (Drama)
- ❑ Wineries of northern Greece
 - ❑ PAVLIDIS Estate (Drama)
 - ❑ NICO LAZARIDI Estate (Drama)
 - ❑ BIBLIA CHORA Estate (Kavala)
- ❑ Company
 - ❑ Euroaction (Thessaloniki)



The project

Budget	€997,292.70 (Public expenses: €931,167.70)
Funding source	Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH – CREATE – INNOVATE (Project code: T1EDK-00300)
Project manager	Professor Vassilis G. Kaburlasos
Start and finish date	June 28, 2018 – February 27, 2021

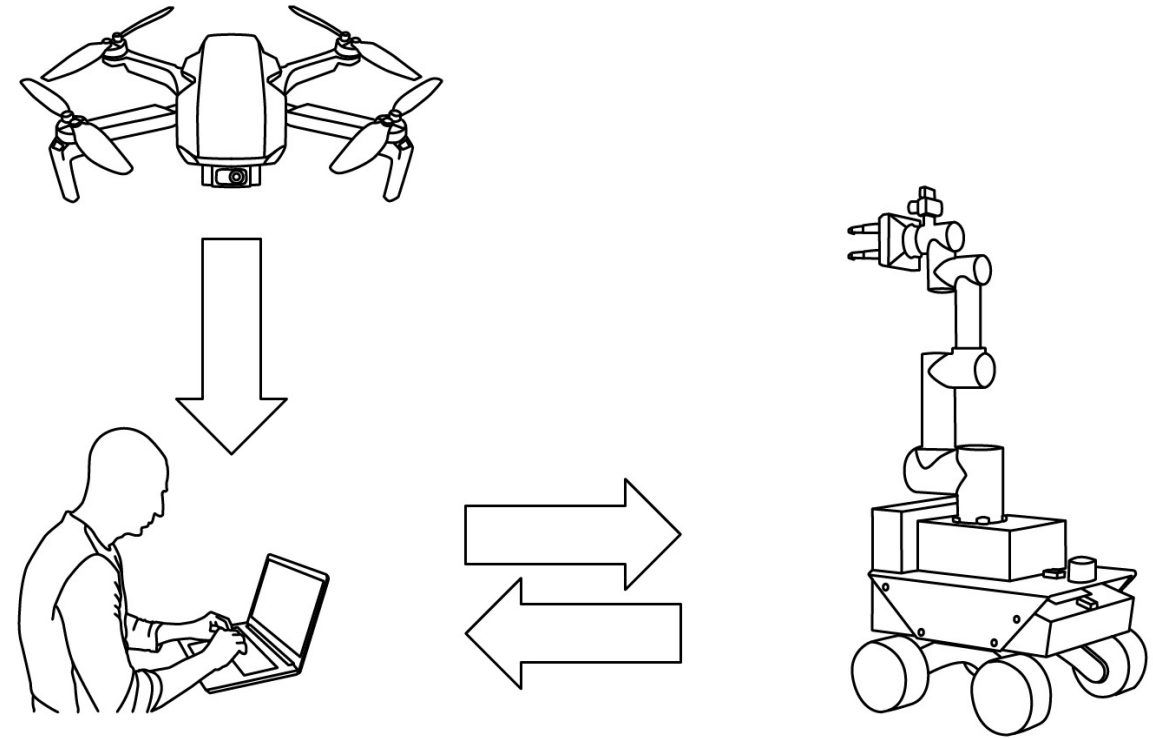
Aims of the project

- ❑ To **develop an “intelligent” wheeled Autonomous Robot** for Grape harvest (ARG, for short) toward mechanizing grape practices:
 - ❑ Harvest: select and harvest grapes of similar degree of ripeness.
 - ❑ Green harvest: selective thinning of grapes to improve the ripening conditions of the rest.
 - ❑ Defoliation: selective leaf removal to modify the microclimate of grapes.
- ❑ To improve the competitiveness of Greek viticulture products in two different manners:
 - ❑ the **increase in quantity** and
 - ❑ the consistent **high quality** of the produced grapes and wines
 - ❑ with a simultaneous **decrease of production cost**.



System architecture

- ❑ The overall system consists of three components:
 - ❑ Unmanned Aerial Vehicle (UAV),
 - ❑ Controller Platform (CP) and
 - ❑ Agrobot (ARG) component
- ❑ The UAV component takes images of the vineyards to be supplied to the CP component. The CP computes the navigation paths and communicates with ARG.



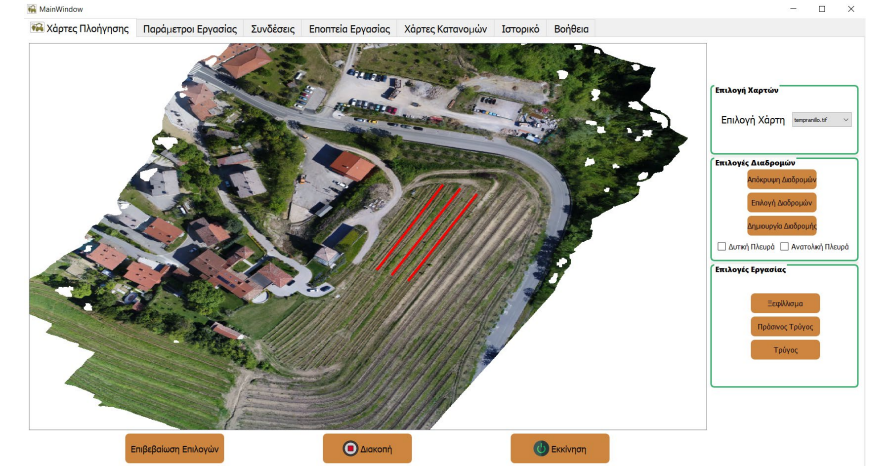
Preliminary work

- ❑ Definition of personalized harvest requirements:
 - ❑ Interviews with oenologists and agronomists.
 - ❑ Definition of system requirements.
 - ❑ Functional specifications.
- ❑ Supply and installation of hardware:
 - ❑ Suitability study of available robot and assistive technologies.
 - ❑ Supply of equipment.
 - ❑ Equipment adjustment.
 - ❑ Construction of ARG.



Main work

- ❑ Vineyards mapping (UAV):
 - ❑ Installation/ learning of UAV software.
 - ❑ Testing flights.
 - ❑ Specific flights.
- ❑ Development of users interface (CP):
 - ❑ Maps management software.
 - ❑ Navigation route generation.
 - ❑ Agricultural tasks personalization.



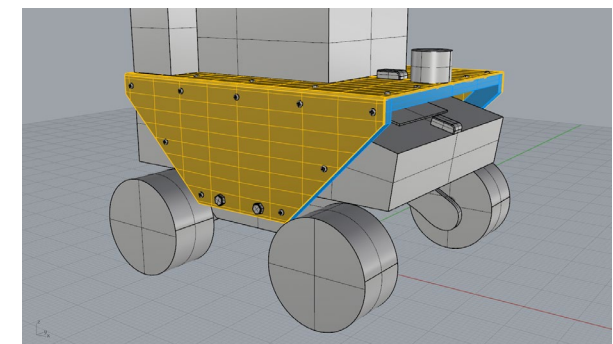
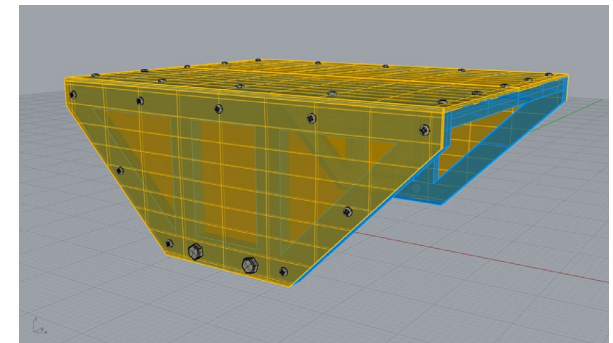
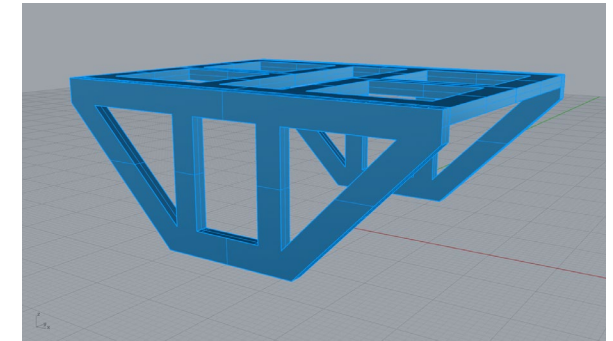
Main work

- ❑ Software development (ARG):
 - ❑ Ground robot.
 - ❑ Robotic arm.
 - ❑ Sensors.
- ❑ Development of sensor data processing and decision making (ARG):
 - ❑ Navigation.
 - ❑ Manipulation.
 - ❑ Computer vision.



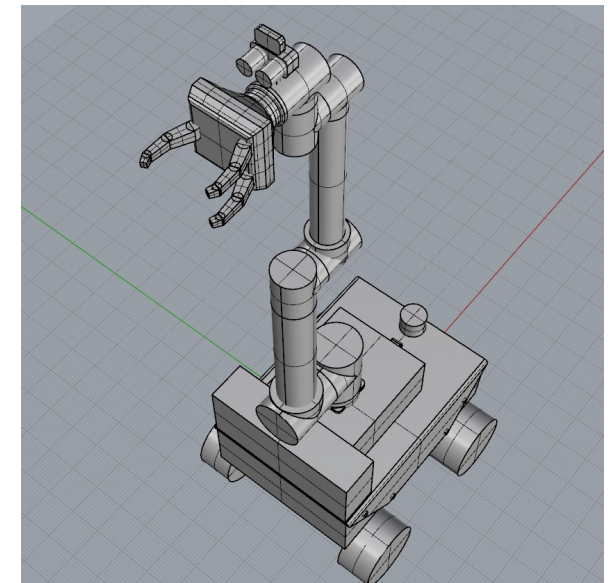
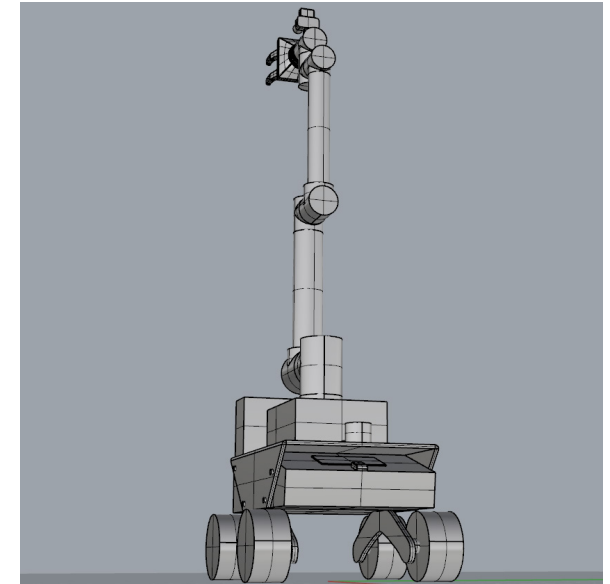
Requirements

- ❑ Viticulture tasks:
 - ❑ The robot must remove carefully and uniformly a percentage of leaves on the crop base, only from the east side of the vineyard (Defoliation).
 - ❑ The robot must remove a percentage of grape clusters from each vine, in a priority order as follows: sick, malnourished, uneven and immature (Green harvest).
 - ❑ The robot must remove all ripened grape clusters and place them in harvesting baskets. Sick/damaged clusters are not collected and either removed or left on the vine (Harvest).



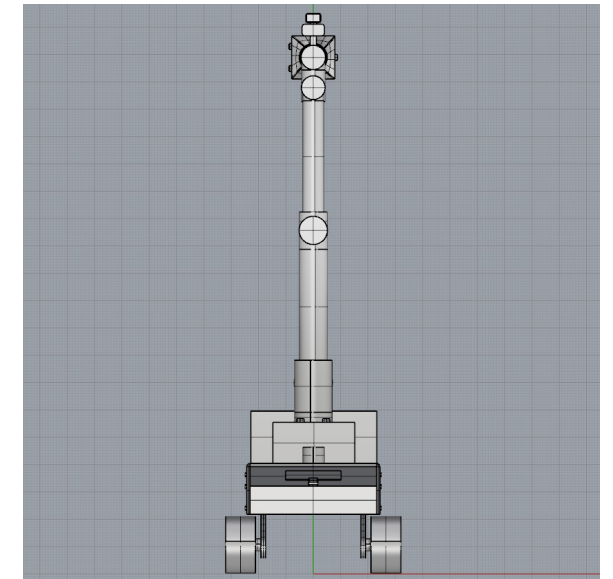
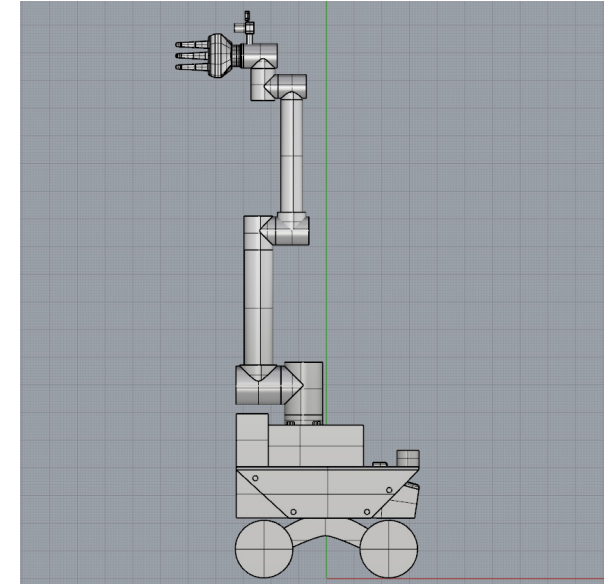
Requirements

- ❑ The robot must be able to understand the physical properties of each object and work under dynamic conditions.
- ❑ The robot first will acquire raw data about the environment, will analyze it and will operate based on its perception.
- ❑ Technically, the Agrobot will be developed by the integration of a wheeled robot, one robot arm, end-effectors such as a cutter, electronic sensors such as cameras, and software that will coordinate the operation of the mechanical and electronic devices.

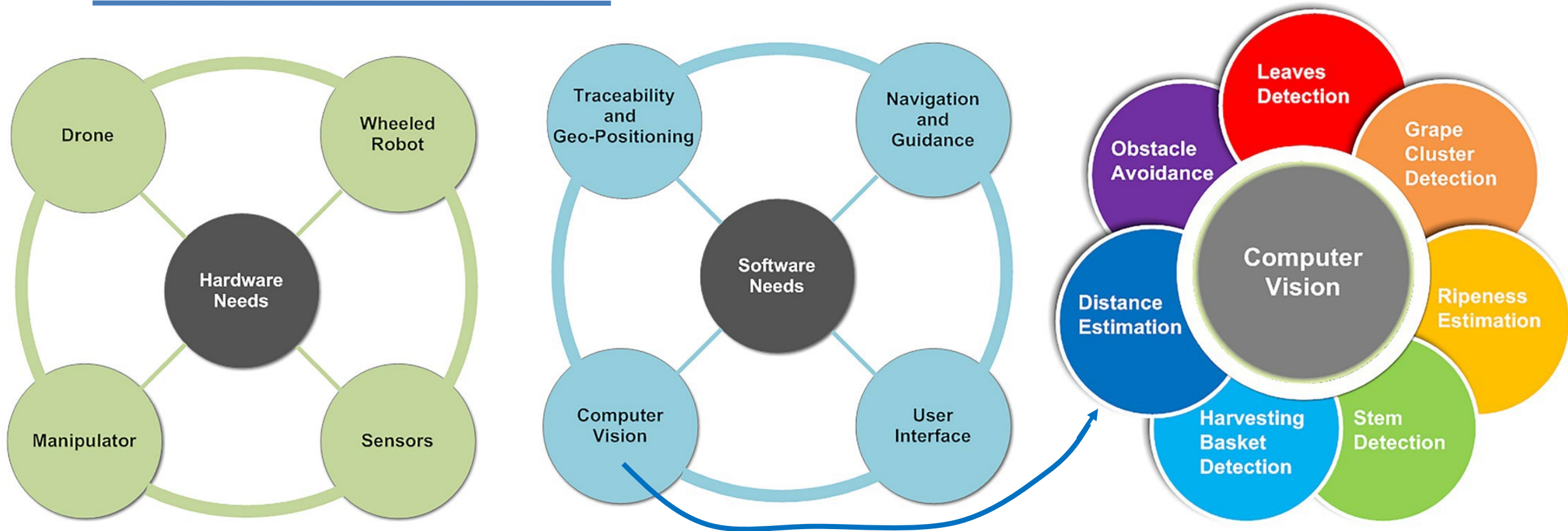


Requirements

- ☐ An aerial drone is needed to contribute to the development of digital maps required autonomous navigation.
- ☐ The robot's sensing system needs to be equipped with specialized manipulators and end-effectors able to work under varying conditions.
- ☐ Effective software needs to be developed so as to ensure robot functionalities and robot applications.
- ☐ Algorithms need to be adaptive and able to deal with object and environment variations.



Technological needs

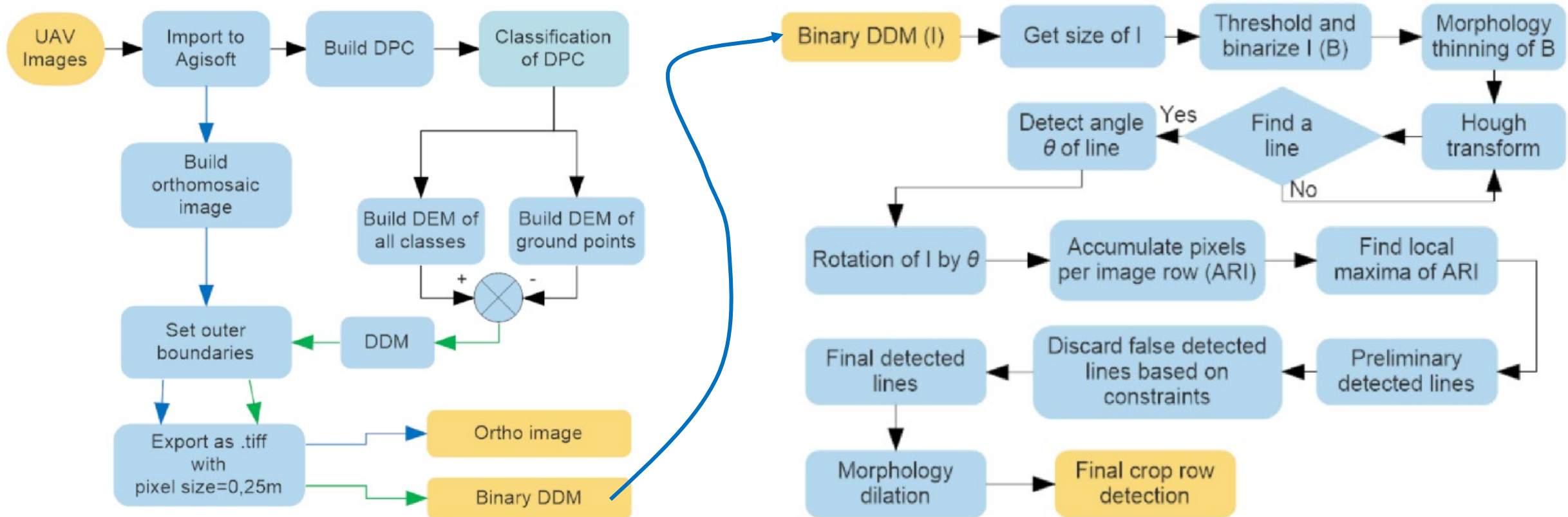


Vineyards mapping (UAV)

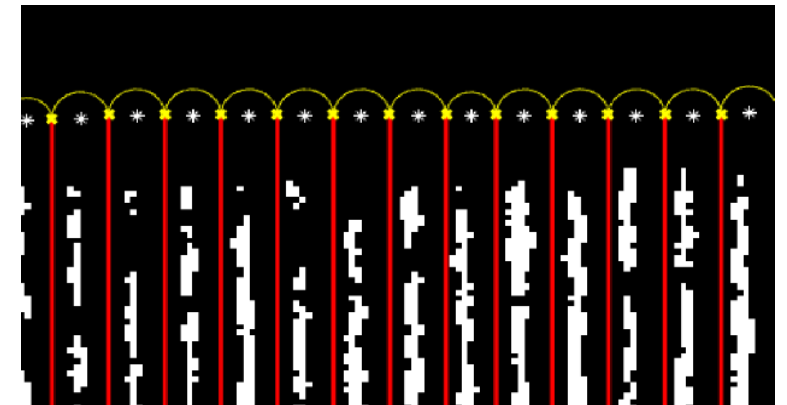
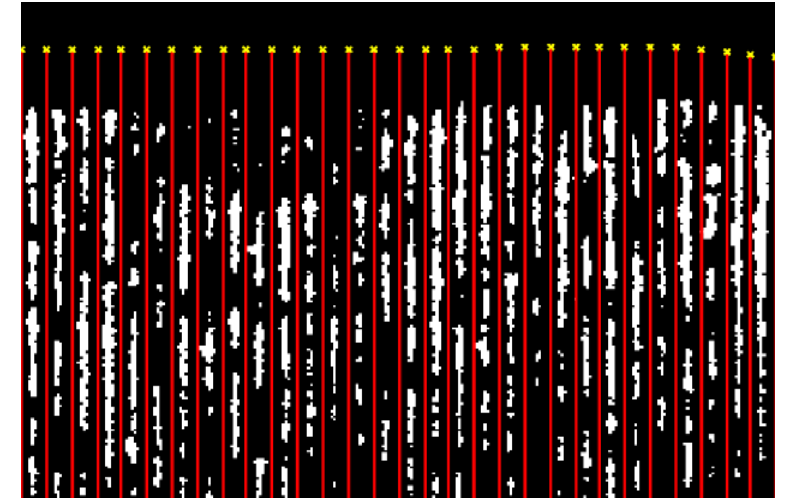
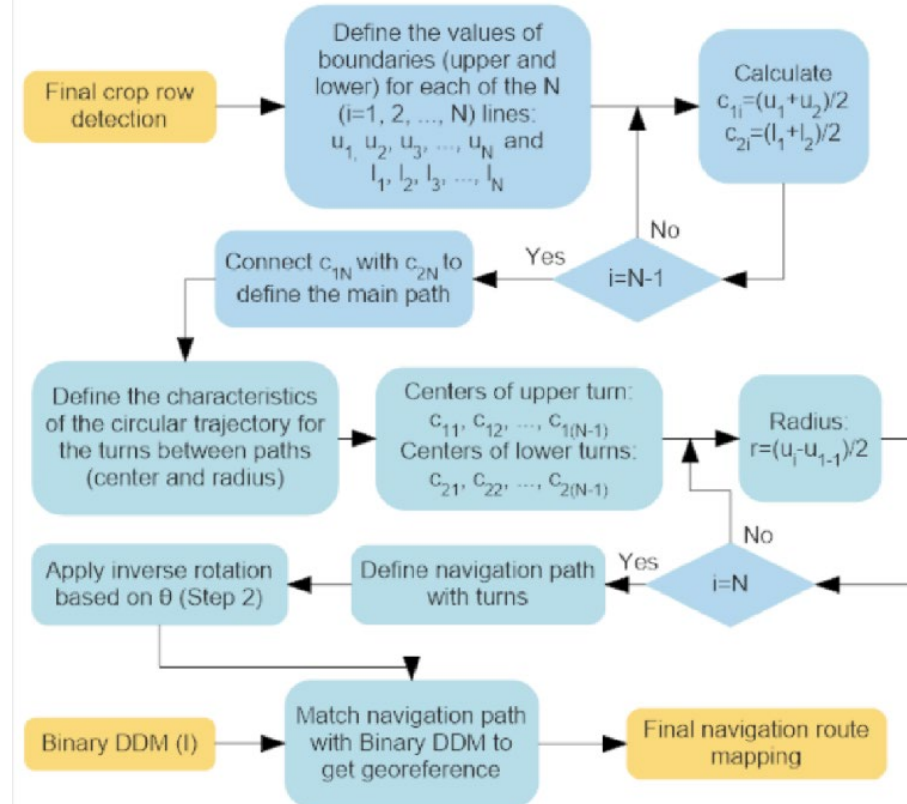
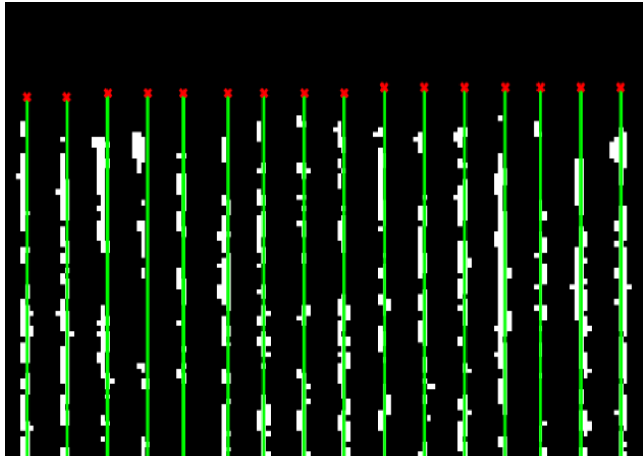
- ❑ A **machine vision functional navigation route mapping** was developed, to guide ARG in the extracted vineyard rows.
- ❑ Use of **RGB images acquired with a UAV**.
- ❑ **Tolerant** to varying illumination, weed and missing plants.
- ❑ **Low processing**, appropriate for real-time applications.
- ❑ **Robust** to different field shapes.



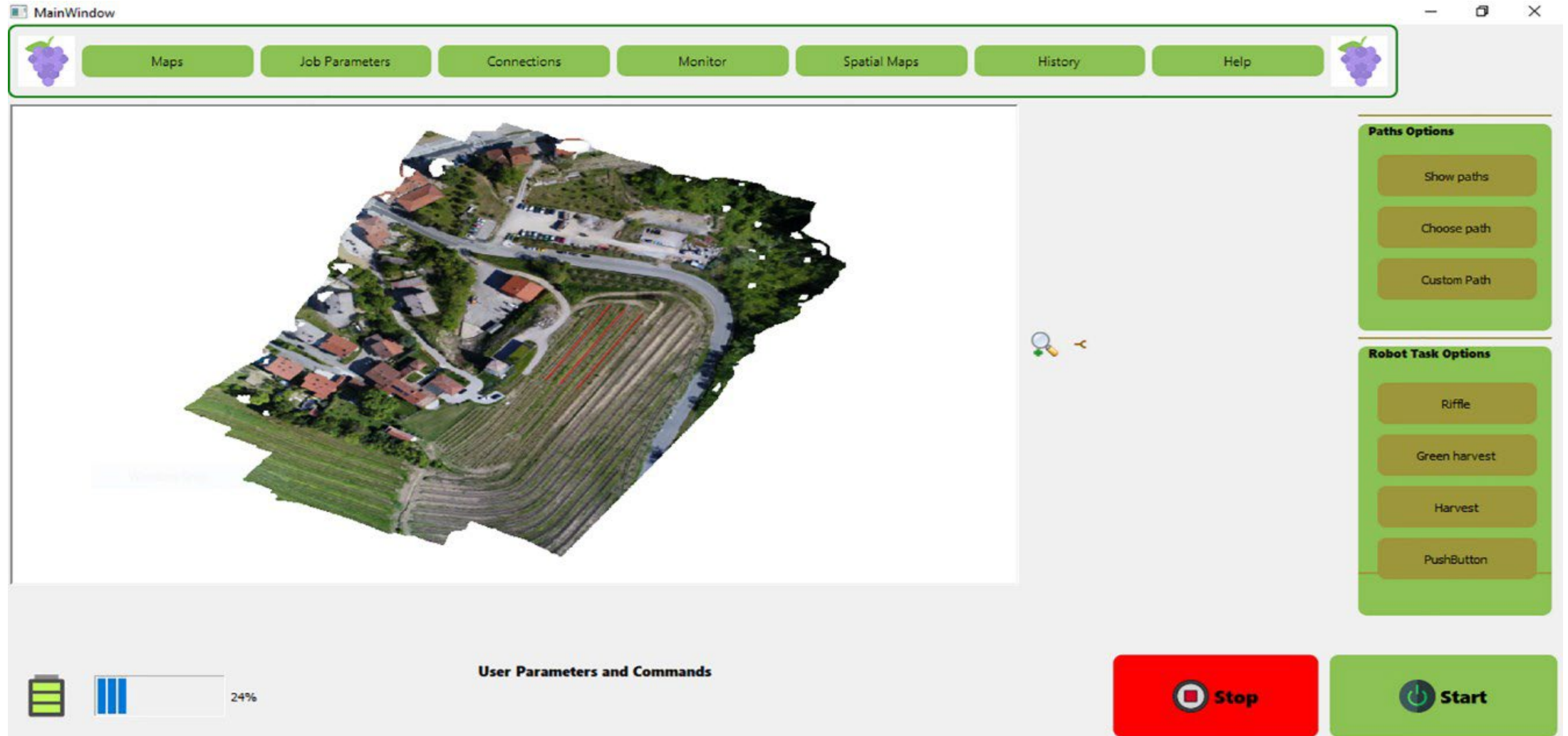
Vineyards mapping (UAV)



Vineyards mapping (UAV)



From UAV to CP



Development of users interface (CP)

☐ Functional specification of the GUI:

- ☐ The users need to Login and have access to vineyard maps of their interest.
- ☐ All actions of the users need to be stored to an individual history file.
- ☐ The administrator needs to register new users and update the application. The administrator can access all maps and history files.
- ☐ The user can see all real-time measurements of the robot and live stream from its cameras, knowing exactly from which part of the vineyard these videos come from.
- ☐ All measurements and video sequences need to be able to get saved in files.
- ☐ Measurements need to be grouped and visualized on the maps in an understandable way.
- ☐ Measurements regarding the status of the robot, such as battery level, the current position of the robot, working time, also need to be displayed.

Development of users interface (CP)

❑ Functional specification of the GUI:

- ❑ The users need to be able to select the agricultural task for the robot and customize the selected task from a setting panel based on their personal practices.
- ❑ The GUI needs to keep a history of the tasks and choices made by the users.
- ❑ Statistics regarding the selected tasks, such as the number of bunches removed, how long the work took to complete, etc., should also be recorded.
- ❑ Since the measurements are numerous, the users need to have the possibility to choose which of the information will be displayed at the screen at any time.
- ❑ It should be possible for the users to check that all the individual components that comprise the robot work properly and are connected to each other.
- ❑ The users need to be able to alternate between their maps and see all possible paths on every stored vineyard map.

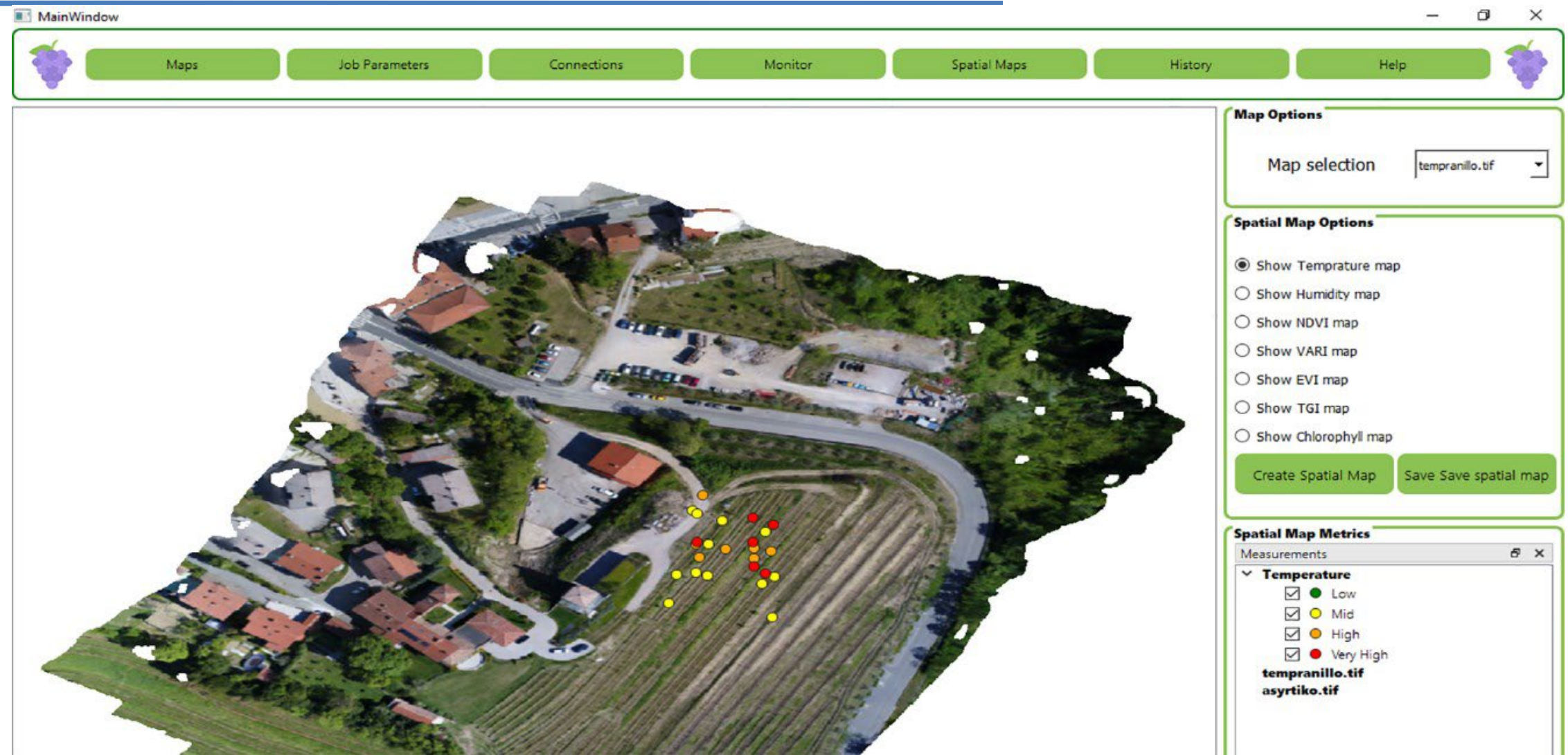


Development of users interface (CP)

❑ Functional specification of the GUI:

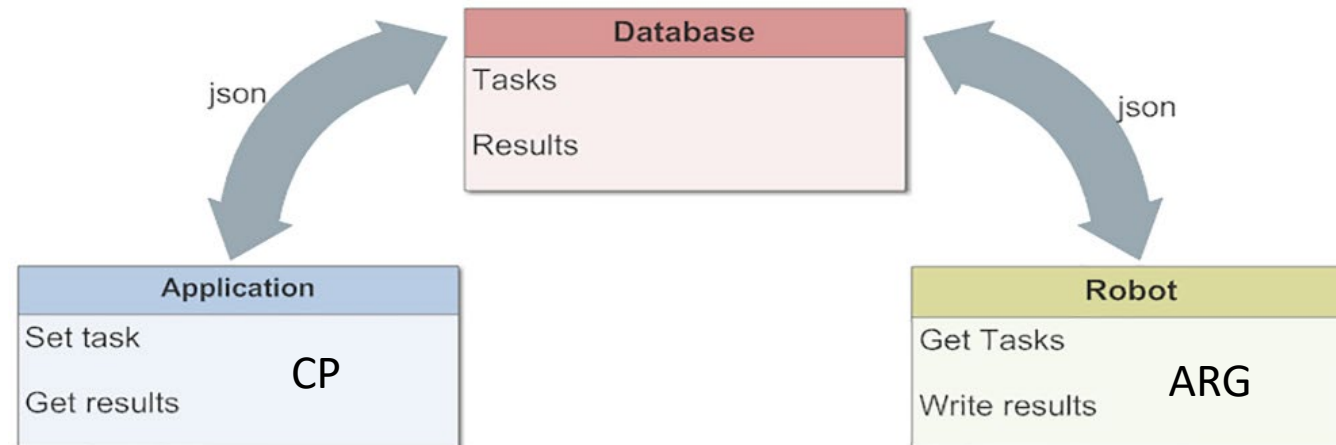
- ❑ The users need to be able to select one or more paths on each map, where the robot should navigate and perform the selected task.
- ❑ If the users do not select a path or specific settings for an agricultural task, then the system will use default settings and perform the tasks on the closest path from its current location.
- ❑ The users need to select the agricultural task to further proceed, so that the system to send their options to the robot and start executing the task.
- ❑ The users need to be able to zoom in/out on the displayed maps so as to clearly inspect the paths and measurements shown on the maps.
- ❑ The users need to be able to give the command to the robot to start a task but also to stop working at any time.

Development of users interface (CP)



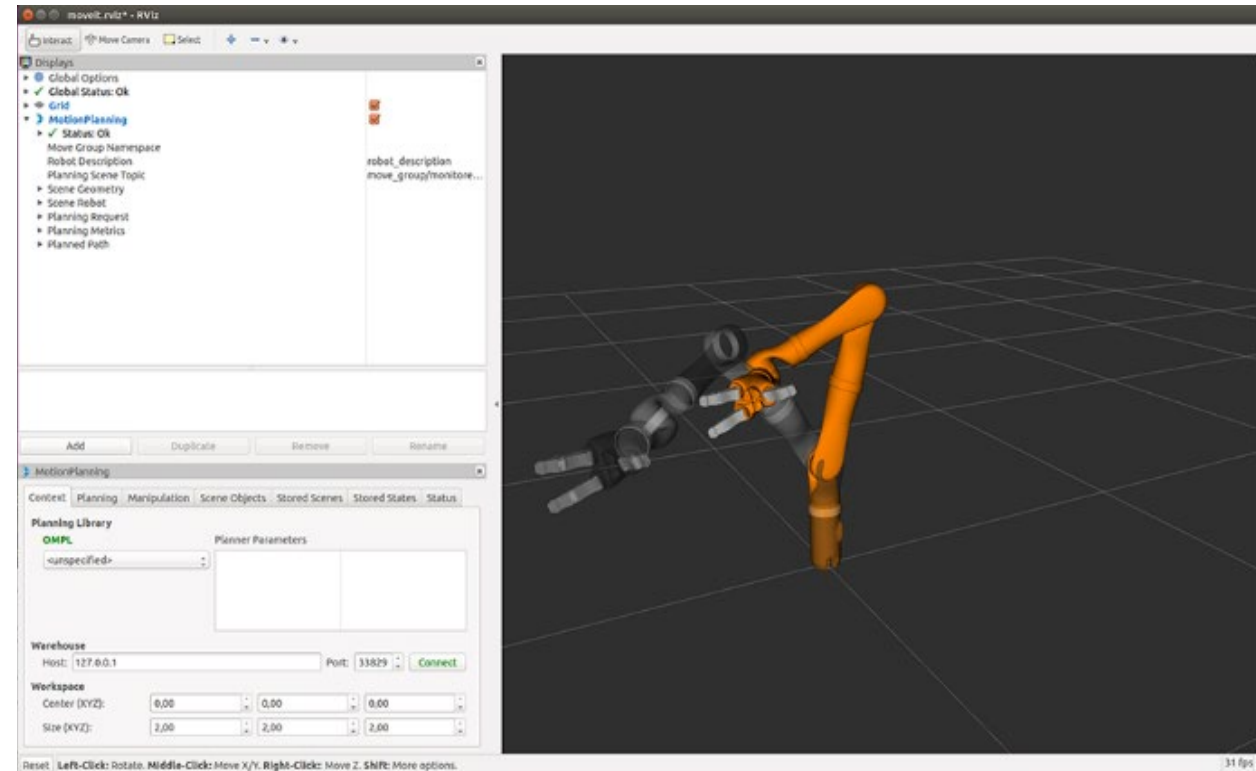
From CP to ARG

- ❑ The robot while functioning, it senses the environment and gathers data. This data has to be sent back to the main computer, to the system's database in real-time to update the GUI for correct decision making by the user.
- ❑ The user needs to send data about the tasks and settings to the robot, stored through the GUI, in the database and transmitted to the robot so as to start or/and stop executing.
- ❑ The robot and the system write and read data to and from the database.
- ❑ In order to set up a real-time communication, between ARG and CP, a Wi-Fi based communication network is established.



Software development (ARG)

- ❑ The complete mathematical forward kinematic analysis and the Robotic Operating System (ROS) simulation modeling of JACO2 robotic manipulator.
- ❑ The accuracy of mathematical computation is cross-validated. The development of the complete mathematical and simulation model of JACO2 robotic arm with **evaluated accuracy**.
- ❑ Both analysis and simulation models are essential in order to **customize the robot for novel applications**, e.g. to perform agricultural operations such as harvest, as part of an autonomous harvesting robot.



Sensor data processing and decision making (ARG)

□ Grapes and leaves segmentation task

Eleven CNN models able to provide semantic segmented images are examined as part of the sensing subsystem of an autonomous agricultural robot.

The task is challenging due to the similar color between grapes, leaves and image's background. Moreover, the lack of controlled lighting conditions results in varying color representation of grapes and leaves.

The studied CNN model architectures combine three different feature learning sub-networks, with five meta-architectures for segmentation purposes.

Investigation on three different datasets consisting of vineyard images of grape clusters and leaves, provided segmentation results, by mean pixel intersection over union (IU) performance index, of up to **87.89% for grape** clusters and **83.45% for leaves**, for MobileNetV2_PSPNet model.

Sensor data processing and decision making (ARG)

□ Grapes and leaves segmentation task

Input RGB image, ground truth image and segmented image.



Sensor data processing and decision making (ARG)

□ Stem segmentation and localization

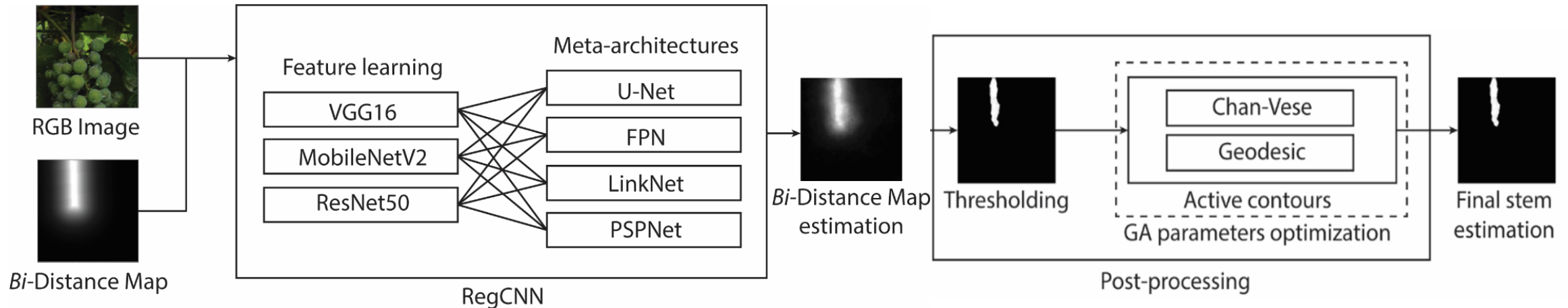
A regression convolutional neural network (RegCNN) is applied to images acquired on-site from the on-board cameras of ARG. Twelve CNN model architectures derived by the combination of three different feature learning sub-networks, with four meta-architectures, are designed to find the most efficient model.

For the first time, stem detection is tackled as a regression problem in a way to alleviate the imbalanced data phenomenon that occurred in the vineyard images. In order to justify the effectiveness of the RegCNN models, the same CNN architectures are tested in a typical classification (ClaCNN) setup. Comparative results reveal that the regression models outperform the classification ones, in two datasets with different characteristics.

Grape bunches stems are detected with an intersection-over-union (IU) performance of up to **98.18%** with RegCNNs, before post-processing optimization. Moreover, by applying a Genetic Algorithm (GA) based parameter tuning mechanism, **optimized post-processing parameters led to an improved IU performance of up to 98.90% for the case of the UNET_MOBILENETV2 model.**

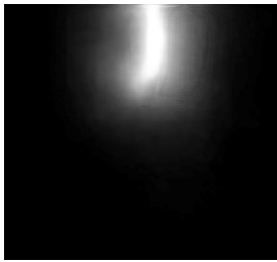
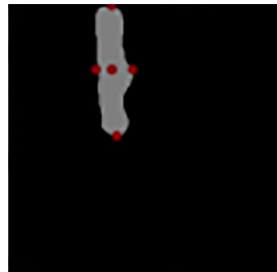
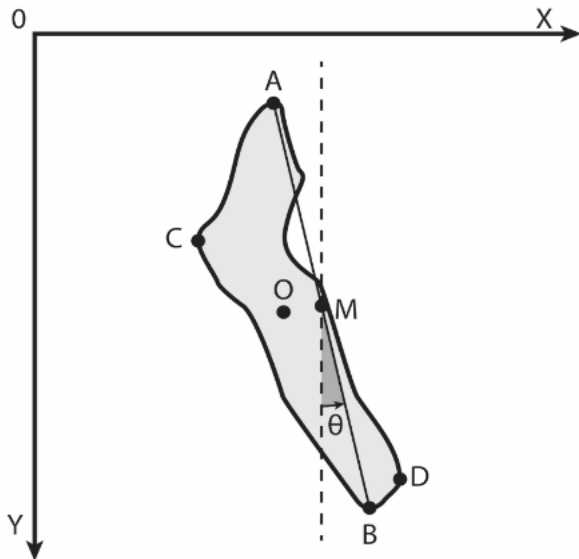
Sensor data processing and decision making (ARG)

□ Stem segmentation and localization



Sensor data processing and decision making (ARG)

□ Stem segmentation and localization



Sensor data processing and decision making (ARG)

□ Vine trunk detection

Dynamically changing agricultural environments provide adverse conditions to robotics operability.

In order to perform the agricultural tasks safely and accurately, reliable landmarks from the surrounding environment need to be identified.

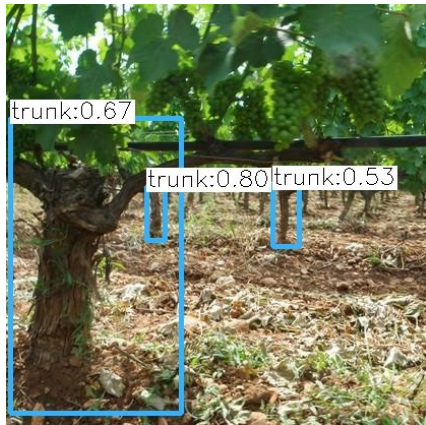
Three deep learning models are employed for accurate and fast detection of high-level features of vineyards, the vine trunks ;Faster regions-convolutional neural network (Faster R-CNN), You Only Look Once version 3 (YOLOv3) and YOLOv5.

Comparative results indicate **YOLOv5** as the configuration that allows the faster and most accurate vine trunk detection, achieving an overall Average Precision (**mAP**) of **73.2% in 29.6 ms**.

Sensor data processing and decision making (ARG)

□ Vine trunk detection

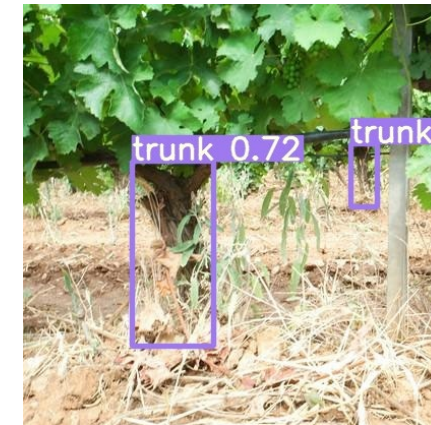
Faster R-CNN



YOLOv3



YOLOv5



Sensor data processing and decision making (ARG)

□ Harvest crates detection

The robot will cut the grape bunches suitable for harvesting and collect them in harvest crates located in the vineyard corridors along its path.

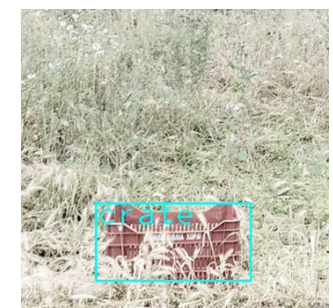
A state-of-the-art algorithm, the You-Only-Look-Once version 3 (YOLOv3), is employed to solve the in-field demanding object detection task, that of harvest crates.

Complicated environment in-field conditions, such as illumination variations, branches and leaves occlusion, weed and object overlapping, make harvest crates detection challenging.

Experimental results verify the effectiveness of the model under varying conditions, providing high recognition accuracy up to **99.74 % (mAP)**.

Sensor data processing and decision making (ARG)

❑ Harvest crates detection



Sensor data processing and decision making (ARG)

□ Ripeness estimation 1

A novel neural network architecture that processes whole histograms induced from digital images.

A histogram (Green of RGB color model) is represented by an Intervals' Number.

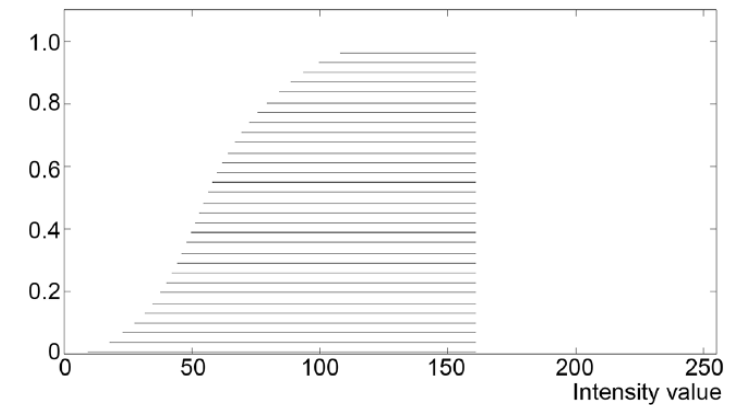
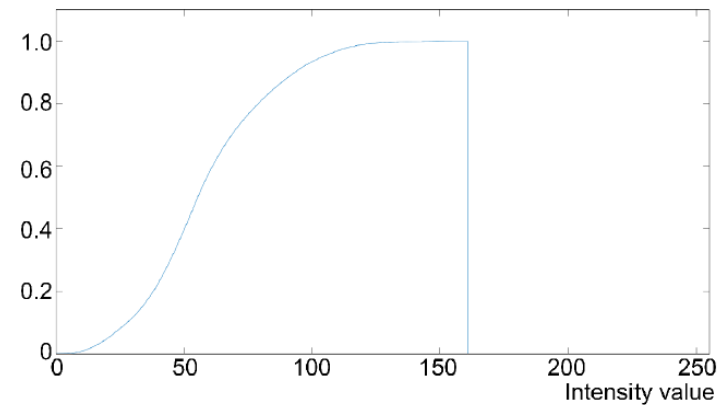
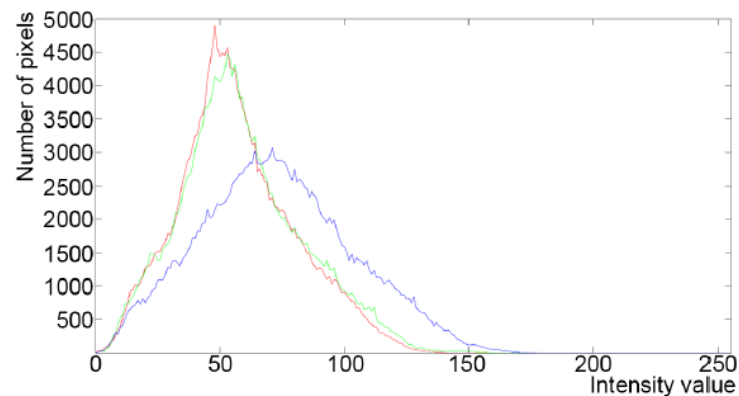
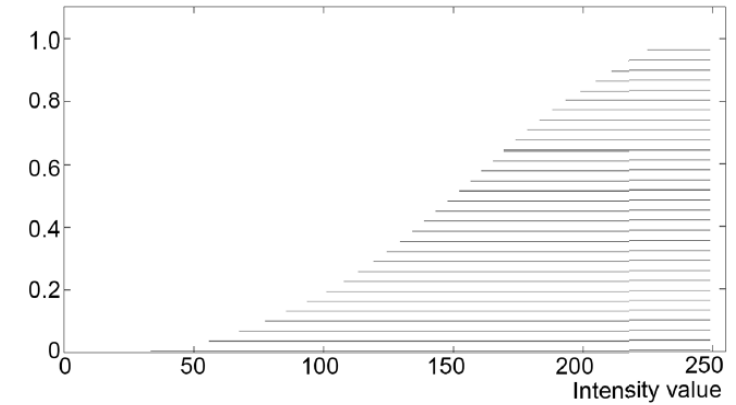
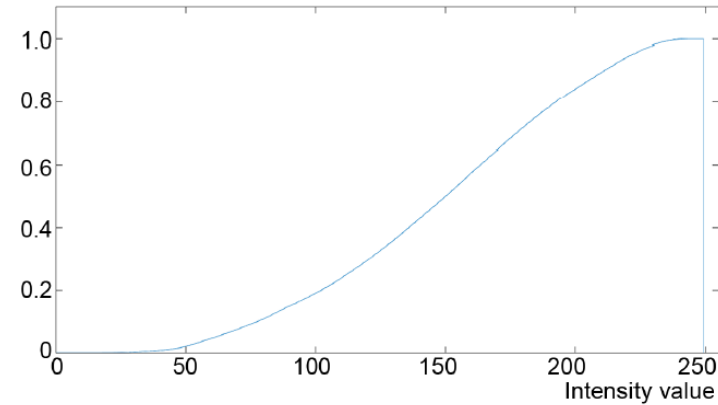
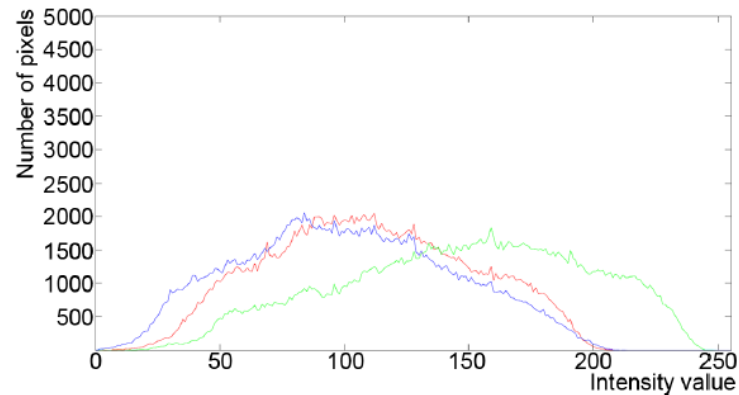
The IN Neural Network” is capable of predicting an IN from past INs.

Application on a time series of digital images of grapes taken during their growth to maturity.



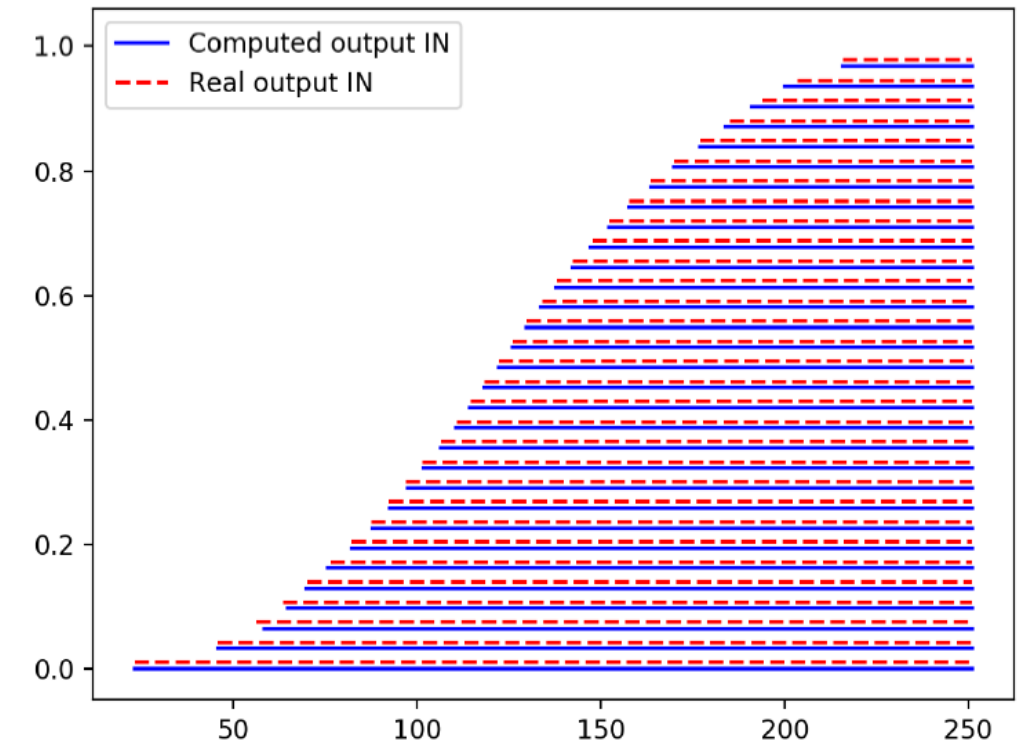
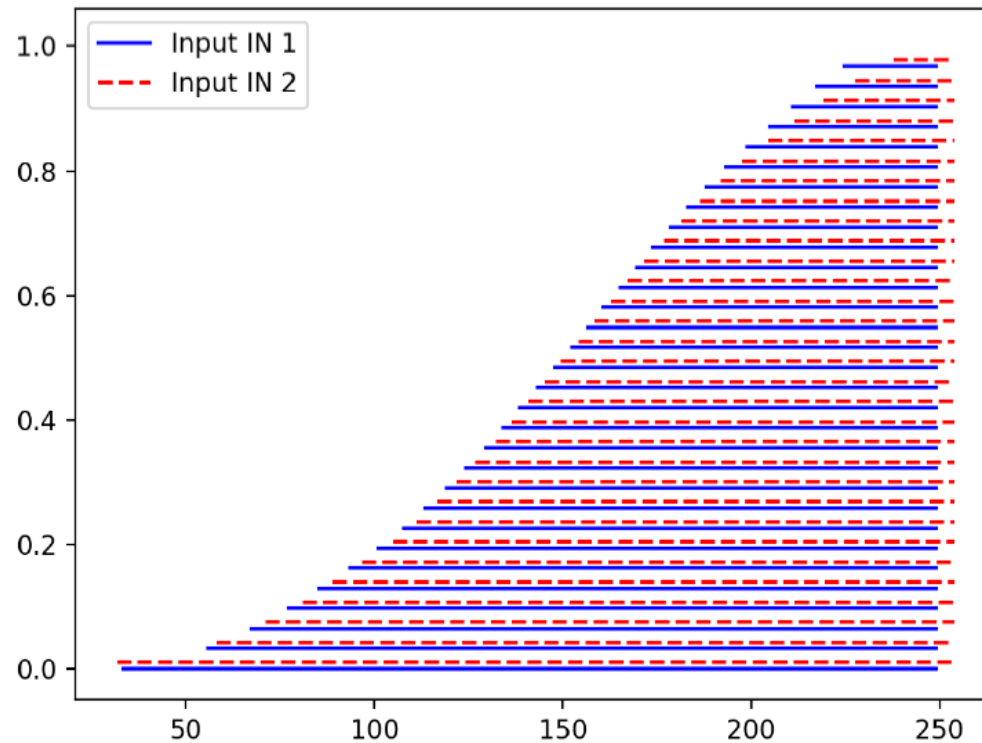
Sensor data processing and decision making (ARG)

□ Ripeness estimation 1



Sensor data processing and decision making (ARG)

□ Ripeness estimation 1

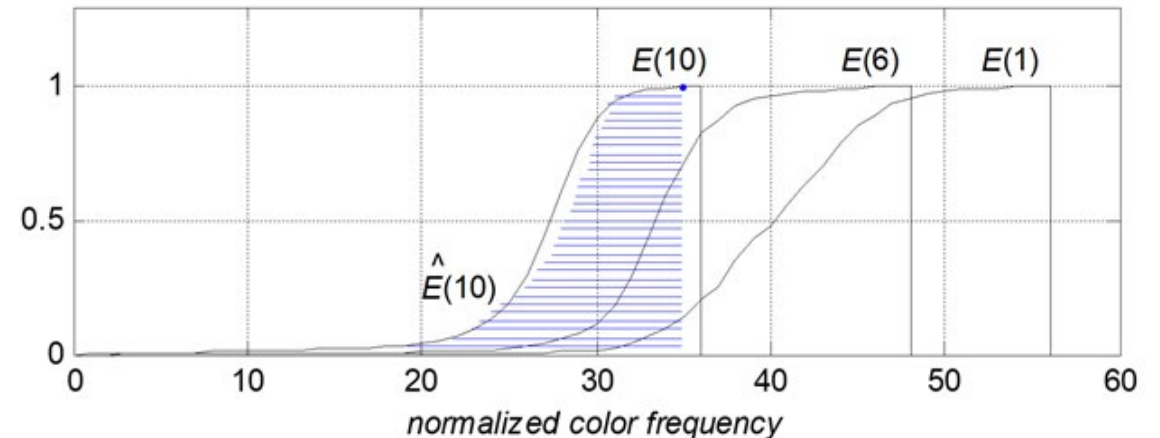


Sensor data processing and decision making (ARG)

□ Ripeness estimation 2

A histogram (Hue of HSV color model) is represented by an Intervals' Number.

Unlike the **RGB** color model, which is hardware-oriented, the **HSV** model is user-oriented, based on the more intuitive appeal of combining hue, saturation, and value elements to create a color.



Data acquisition

- ❑ For the **UAV** imagery acquisition it was used a SAMSUNG NX500 digital camera with resolution 6480×4320. The focal length of adopted lens was about 16 mm. The ground flying height was at 30 meters and the nominal ground sampling distance (GSD) was 0,25 cm. The acquired images were stored in a memory card using JPEG image format. The UAV completed 8 flights, covering a total area of about 137.000 m² of 6 selected grape varieties; 3 red and 3 white. **The total number of acquired images was 836.**
- ❑ For the **grapes and leaves segmentation** task two datasets were used. Dataset 1 consisted of 274 images of white grapes, containing 1064 white grape clusters and 1192 leaves, augmented to 1370. Dataset 2 consisted of 259 images of red grapes, containing 1282 red grape clusters and 1264 leaves, augmented to 1295. Images of dataset 1 were captured by an RGB high resolution Samsung Mirrorless camera (NX500), while images of dataset 2 were captured by a USB 3.0 high resolution Thorlabs camera (DCC3240C) with lens C-MOUNT 12 mm (MVL12M23). **The total number of images was 2665 images.**
- ❑ For the **stem segmentation** task, two datasets were used: ImBa-Dataset and Ba-Dataset. The total training and testing images increased to 1070 and 110 for the ImBa-Dataset (from 214 and 22), while for the Ba-Dataset increased to 1000 and 110, respectively (from 200 and 22). **The total number of images was 2290 images.**
- ❑ For the **harvest crate** detection task, 920 target images were acquired; 520 for training and 400 for testing. Three data augmentation techniques were used to expand the training dataset to 2080 images. The testing involved 400 images unknown to the network, forming a **final dataset of 2480 images** in total.

Data acquisition

- ❑ For the **vine trunks** detection task, all images were captured by an RGB high resolution Samsung NX500 Mirrorless camera. The original dataset consisted of 899 different images. The original dataset was augmented, forming a final training dataset of 2516 images (629 original and 1887 augmented). For the validation and testing of the models were used 180 and 90 images, respectively. **The total number of acquired images was 2786.**
- ❑ For the **ripeness estimation** task, the dataset consisted of **517 images**, from 6 different grape varieties, 3 red (tempranillo, merlot, cabernet sauvignon) and 3 white (assyrtiko, sauvignon blanc, vidiano), from veraison to harvest time. Image acquisition was accompanied by sampling and chemical analyzes to extract maturity indices correlated to the acquired images. Image acquisition and sampling lasted from July 27 to 14 September. Digital images of specific grapes were taken at the same time of a day from specific position (i.e. height/angle) in front of a grape bunch, 10 bunches for every variety. The sampling period was selected equal to 7 days during first 3-4 weeks; whereas, it was equal to 3 days, later, until harvest time. All images had a resolution of 4320×6480 pixels, 350 dpi and 24-bit color depth stored in .jpeg format.

Data acquisition

- ❑ Image acquisition is in line with ARG’s function:
 - ❑ The robot will navigate between the vineyard corridors, seek for the closest vine trunk on its right side using the mounted camera on the robotic arm, will stop in front of the detected vine trunk and perform one of the three selected tasks; harvest, green harvest or defoliation, placing the removed bunches in the closest harvest crate along the corridors.
- ❑ For all in-house images, the selected capturing height was in line with the dimensions of the wheeled harvesting robot, taking into account the average size and maximum opening angles of the mounted robotic arm; thus, all images were captured between a **height of 50 cm to 150 cm** and from a **distance between 30 cm and 100 cm** from the vine rows.
- ❑ All images were taken under natural daylight including disturbances such as varying illumination, wild vegetation, occlusions and shadowing.







Related published work

Conference proceedings:

1. Kalampokas, T.; Tziridis, K.; Nikolaou, A.; Vrochidou, E.; Papakostas, G.A.; Pachidis, T.; Kaburlasos, V.G. Semantic Segmentation of Vineyard Images Using Convolutional Neural Networks. In *21st International Conference on Engineering Applications of Neural Networks (EANN 2020)*; 2020; pp. 292–303.
2. Kaburlasos, V.G.; Vrochidou, E.; Panagiotopoulos, F.; Aitsidis, C.; Jaki, A. Time Series Classification in Cyber-Physical System Applications by Intervals’ Numbers Techniques. In *Proceedings of the 2019 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*; IEEE: New Orleans, 2019; pp. 1–6.
3. Badeka, E.; Kalabokas, T.; Tziridis, K.; Nicolaou, A.; Vrochidou, E.; Mavridou, E.; Papakostas, G.A.; Pachidis, T. Grapes Visual Segmentation for Harvesting Robots Using Local Texture Descriptors. In *Proceedings of the 12th International Conference on Computer Vision Systems (ICVS 2019)*; Thessaloniki, 2019; pp. 98–109.
4. Kaburlasos, V. G.; Vrochidou, E.; Lytridis, C.; Papakostas, G. A.; Pachidis, T.; Manios, M.; Mamalis, S.; Merou, T.; Koundouras, S.; Theocharis, S.; Siavalas, G.; Sgouros, C.; Kyriakidis, P.
5. Toward Big Data Manipulation for Grape Harvest Time Prediction by Intervals’ Numbers Techniques. In *proceedings of the 2020 International Joint Conference on Neural Networks (IJCNN)*; Glasgow, United Kingdom, 2020, pp. 1-6.



Related published work

6. Badeka, E.; Vrochidou, E.; Tziridis, K.; Nicolaou, A.; Papakostas, G.A.; Pachidis, T.; Kaburlasos, V.G. Navigation route mapping for harvesting robots in vineyards using UAV-based remote sensing, In Proceedings of the 10th IEEE International Conference on Intelligent Systems (IS'20); Varna, Bulgaria, 2020; pp. 171–177.
7. Theodore Pachidis, Christos Sgouros, Vassilis G. Kaburlasos, Eleni Vrochidou, Theofanis Kalampokas, Konstantinos Tziridis, Alexandros Nikolaou, George A. Papakostas, “Forward Kinematic Analysis of JACO2 Robotic Arm Towards Implementing a Grapes Harvesting Robot”, The 28th International Conference on Software, Telecommunications and Computer Networks (SoftCOM 2020), 17-19 September, Hvar, Croatia
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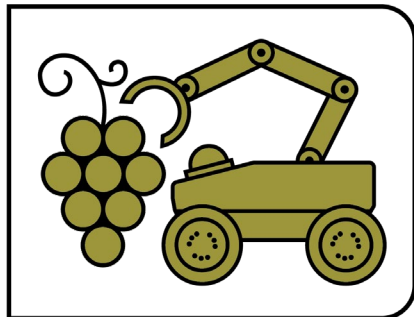
Future work

- ☐ 3 journal papers, 1 conference article, 1 patent ongoing.
- ☐ 2 journal papers and 1 patent to complete the deliverables.
- ☐ Navigation tests.
- ☐ Integration of all systems.
- ☐ Fine-tuning.
- ☐ In-field testing.



Acknowledgement

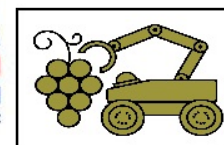
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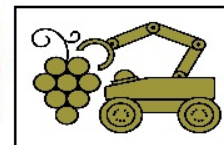
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Thank you!



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