The *AgriRover*: a Reinvented Mechatronic Platform from Space Robotics for Precision Farming

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Abstract This paper presents an investigation of a novel development of a multi-functional mobile platform for agriculture applications. This is achieved through a reinvention process of a mechatronic design by spinning off space robotic technologies in terrestrial applications in the AgriRover project. The AgriRover prototype is the first of its kind in exploiting and applying space robotic technologies in precision farming. To optimize energy consumption of the mobile platform, a new dynamic total cost of transport algorithm is proposed and validated. An autonomous navigation system has been developed to enable the AgriRover to operate safely in unstructured farming environments. An object recognition algorithm specific to agriculture- has been investigated and implemented. A novel soil sample collecting mechanism has been designed and prototyped for on-board and in-situ soil quality measurement. The design of the whole system has benefited from the use of a mechatronic design process known as the Tiv model through which a planetary exploration rover is reinvented into the AgriRover for agricultural applications. The AgriRover system has gone through three sets of field trials in the UK and some of these results are reported.

Introduction

Space exploration missions have captured people's imagination since Neil Armstrong and Edwin Aldrin landed on the moon on 20th July 1969. Armstrong's first walk on the moon demonstrated the possibilities for space exploration, and many following missions were successfully implemented. This human endeavour contin-

ues with a variety of missions such as the exploration of Mars by the *Curiosity* robotic rover. Space robotics were initially developed for specific space missions, for instance the *Canadarm* space robotic manipulators, designed for the Space Shuttle and deployed at the International Space Station.

More recently, European stakeholders have developed the *Strategic Research Cluster in Space Robotics* to support an ambitious space robotics programme. The first batch of funding comprised five common building block projects, supported by the *PERASPERA*[1] Programme Support Activity. These include

1. *ESROCOS*[2]: the design and development of a space robot control operating system ;
2. *ERGO*[3]: a goal oriented autonomous controller
3. *InFuse*[4]: a common data fusion framework;
4. *I3DS*[5]: an integrated 3D sensor suite;
5. *SIROM*[6]: a standard and modular interface for robotic handling of payloads.

Back on earth, agriculture is a vital industry with a world population in 2015 of 7.3 billion, projected to rise to 8.5 billion by 2030. With increasing demands for better quality of food from a growing middle class population and a requirement for more food by the increasing population, world agriculture has entered a new era characterized by the following challenges:

- Long term demands for sustainable food production.
- Monitoring crops at the required level of resolution for better crop production, as well as the urgent need for mobile monitoring platforms which can provide measurements of soil fertility in-situ and in real-time for precision farming. A technological solution is required to meet these challenges and enable the delivery of fertilisers with minimal environmental impacts.

These requirements can be met by recent technological developments such as earth observation, precision farming and agricultural robotics. One particular effort is through a reinvention of some of the technologies developed for space robotics that is reported in this chapter.

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[1] Plan European Roadmap & Activities for Space Exploitation of Robotics & Autonomy @ www.h2020-peraspera.eu

[2] European Space Robot Control Operating System @ www.h2020-esrocos.eu/

[3] European Robotic Goal-Oriented Autonomous Controller (ERGO) @ www.h2020-ergo.eu/

[4] Infusing Data Fusion in Space Robotics @ www.h2020-infuse.eu/

[5] Integrated 3D Sensors @ http://i3ds-h2020.eu/

[6] Standard Interface for Robotic Manipulation of Payloads in Future Space Missions@ www.h2020-sirom.eu/

Soil quality measurement challenge

Soil quality is a key indicator of the fertility level of soil and its measurement has been mostly manual until now. Due to the large areas dedicated to farming, the current practice in many countries, including for instance in the UK and China, is either to:

1. Measure nutrients such as nitrogen, potassium and phosphate at relatively infrequent intervals, perhaps once every two years, using human operators, with typically 100 metre resolution

or

2. Measure at much lower spatial resolution through indirect soil nutrient measurement using remote sensing of the leaf area index of a plant's canopy.

A good understanding of soil fertility is critical for precision farming as this provides the key information to map the targeted farm land, and therefore to optimize the distribution of fertiliser within a field and to select the right type of fertiliser at the right time and at the right intervals.

Satellite data derived systems have already been used for soil quality monitoring with model based calibration. However, in-situ point measurements are still the most common technique used in agricultural, though some ground vehicles are also used on an ad-hoc basis. Satellite data are then primarily used for research investigations. The feedback from end users is that both the spatial and temporal resolution of satellite based monitoring are still not adequate for precision farming. Specifically, the data acquisition rate cannot meet agricultural production demands. Nevertheless, manual measurement precision is not reliable and objective.

To make remote sensing techniques more widely available and usable for soil quality measurement, it is essential to have frequent and reliable calibration data, related to larger areas in order to support the satellite based modelling and predictions. The current challenges for earth observation modelling are related to a lack of this readily available calibration data.

To address the above challenges, it is believed that space based robotics such as *ExoMars* or *Curiosity* rover could offer alternative solutions and be used as a basis for reinvention of a novel solution to revolutionise soil monitoring practice. New mechatronic systems derived or repurposed from space robotics could potentially be used for the automation of the data acquisition of soil fertility and quality measurement. Subsequently, this data could be used as the baseline data or ground truth for the calibration of satellite imagery data. This approach to generating real ground truth data and model driven data to cover large areas is believed to create a step change to achieve the required spatial and temporal resolution for precision farming.

Current soil monitoring technologies

One basic task that can be automated on a farm is soil monitoring along with and in addition to ground coverage such as ploughing, planting and harvesting [1]. Ploughing and planting involves heavy equipment and many farmers have indicated a preference to do it personally because of the need to manage a field. Many mechanisms, have been developed specifically for tasks such as harvesting, but the success of such systems remains at only around 66%, with fruit damage occurring on average in 5% of cases and an average cycle time of 33s [2]. While a number of robots have been designed and deployed to enable the monitoring and treatment of crops for precision agriculture applications, many of them did not move beyond the prototype stage. Successful agricultural robots will need to meet stringent cost requirements to be affordable while performing a successful fusion of global and local reference data to navigate real fields autonomously [3]. This technical need could potentially be fulfilled through reinvention by adapting and deploying mapping and navigation technologies available for planetary rovers in space robotics.

One of the first agricultural mobile robots was *AU-RORA*, but its sensor system restricted it to the interior of greenhouses [4]. This was a small skid-steered inspection robot that integrated a monocular camera and GPS receiver for simple automated inspection duties across an entire field as described by Bengochea-Guevara *et al* [5]. The use of monocular vision simplifies the image processing, but does not support making detailed maps of tall crops or navigation of overgrown areas of farmland. Asstrand & Baerveldt describe another mobile robot with monocular vision for weeding that was developed on a similar platform [6]. Also, precise vehicular control requires wheel rotation steering and path control such as set out by Zhu *et al* [7].

A reinvented mechatronics mobile platform design

AgriRover *System Requirements and Architecture*

Based on analysis of soil fertility monitoring through talking to various stakeholders, including farmers and operators working in fertilisation stations both in the UK and China, the following requirements have been captured:

- Affordability for farmers;
- Intelligent behaviour;
- Robust design: rugged design for outdoors all-weather agricultural use;
- Soil sensing capability;

- Multi-functional manipulation for monitoring, watering and fruit picking;
- Small footprint: To allow the robot to fit in tramlines and between rows of crop (designed for Maze or Wheat) without damaging the crops;
- Payload capability: The platform is required to carry at least two instruments. It should also be able to interface with them where needed;
- Functional but aesthetically pleasing design.

Using a mechatronic design methodology referred to as the *Tiv* model [8], the research team proposed a system architecture which consists of four key hardware blocks as shown in Fig. 1. The independently driven four wheel mechanism, the soil sensing system, navigation sensing suite and the haptic robotic arm system design is based on the analyses of space robotic systems such as *ExoMars* and *Curiosity* rovers. These will ensure that the wheels can be independently controlled to cope with unstructured and challenging terrain. The haptic robotic arm system module is designed to enable a farmer to remotely control the arm so that the system can help farmers to manipulate an end-effector to harvest in a confined environment, such as humid and hot greenhouses. The soil drilling mechanism is derived from deploying space robotic working experience from partners and considering the similarity and differences between planetary soil and farming soil. A drill has been designed to capture soil from a recommended depth of 10 cm to 30 cm into the ground in order to determine the critical section of the soil for crop growth.

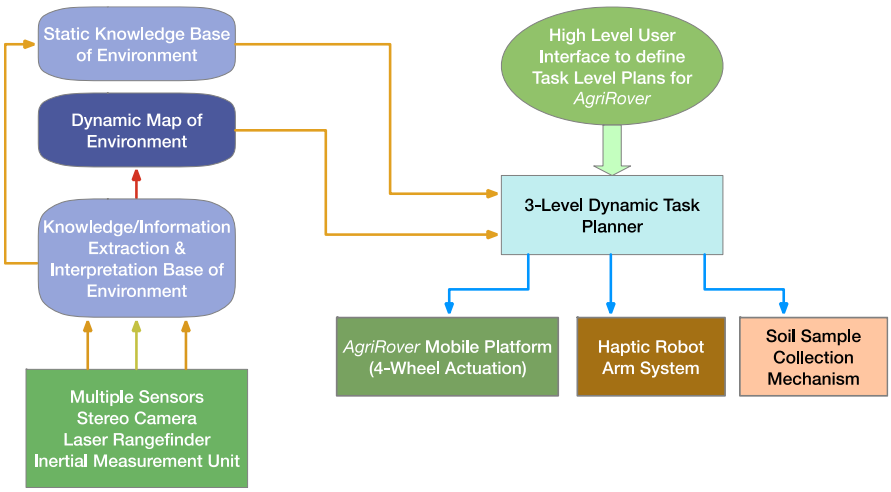


Fig. 1. *AgriRover* system architecture

From these four hardware blocks, the *AgriRover* architecture is then abstracted to create the intelligent behaviour of the mechatronic system design. This is undertaken by creating a three-level dynamic task planner framework so that intelligence of the system is enabled at individual level or combination of control strategies at

three levels. At the on-board computer level, the *AgriRover* can enhance its navigation and environment perception using the existing knowledge base and the dynamically changing map of the environment through the updating of the newly recognised environment. The *AgriRover* can undertake more analysis at The Cloud level, where knowledge relating the crops historical data can be accessed to enhance *AgriRover*'s behaviour. This elevation of the intelligence of the *AgriRover* system from typical mechatronic to the on-board level on to the Cloud level is a key aspect of the reinvention of a traditional mechatronic rover to a Cloud-based intelligent mobile platform.

This reinvention is further enhanced by deploying multiple sensors, namely LIDAR, ultrasonic sensing, dual GPS, a 3-D camera system and wheel torque sensing. The *AgriRover* is enhanced further with a touch pad and mobile user interaction capability to facilitate use. Finally, the mobile platform is supported by two task specific actuation modules: a haptic robotic arm system and a mechatronic soil sample collection mechanism.

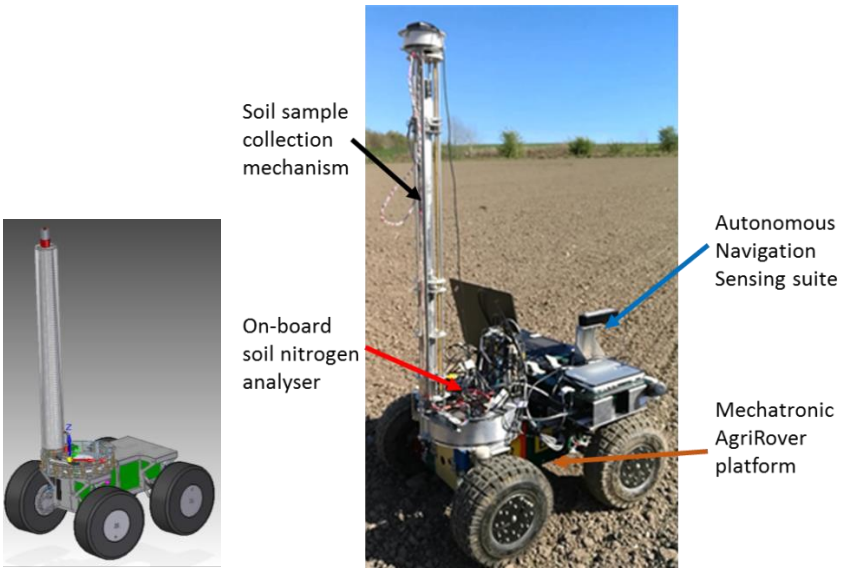
Agricultural Object Recognition

Object recognition has been investigated in space and other applications for several decades and even with the latest hardware technologies, vision based object recognition in agriculture remains a major challenge in computer vision. Various techniques have been studied to address this challenge, these including fusion of images and other data[9], matching of image characteristic points[10], to bags of words of features descriptors [11] and 2D image analysis to 3D point cloud processing. Among these techniques, pixel labelling allows simultaneous detection, classification and localization of objects within a 2D image.

Classification of agricultural features such as crop and plant identification have been a key challenge in automatic control, and machine learning techniques based on recognition of colours and some shapes have been developed by Yan *et al* **Error! Reference source not found.**.

The Reinvention process and the *AgriRover* - Sensing Mobile Platform

Progressing from the conceptual design stage of the *Tiv* model to the detailed design stage through multi-perspective modelling and simulation, a prototype *AgriRover* system has been constructed. It has two modes of operation, namely *AgriRover*-Sensing for soil nitrogen measurement and *AgriRover*-Harvester for selective harvesting. This paper focuses on the first mode of operation and its major components are shown in Fig. 2.



(a) (b)

Fig. 2. One of the initial concepts (a) and (b) the final *AgriRover* platform system prototype with the main featured subsystems

The *AgriRover*- Sensing mobile platform technology is inspired by space robotic research in planetary exploration, represented by the *ExoMars* rover. It addresses the specific needs of soil quality monitoring inspired by on-board chemical analyser *ChMin* on *Curiosity*. The platform technologies comprise a four wheel mobility structure, rover control architecture, soil sample collection mechanism and a user interface for high level rover control and monitoring.

An holistic and systematic approach has been taken in the process of repurposing a mechatronic system *AgriRover* inspired by space robotics. Reinvention of mechatronics in this context is defined as a holistic and systematic process of creating a new mechatronic solution for a defined application, e.g. agriculture, by exploiting and adapting the technical solutions produced in space robotic research. The process builds on the traditional mechatronic design process as represented by the integration of mechanical, electrical and control disciplines. In addition, the advanced computer vision based systems, sensing systems and communication systems accessing information from the Cloud have been deployed in order to enable the system to achieve significantly enhanced intelligence in interacting with intended objects or performing purposeful interventions within its environment.

Four independently driven wheeled platform design

The following requirements offer guidance to the mechatronic reinvention effort:

- Long operational time - The robot is required to run for 8 hours in a field from a suitable power source.
- Affordability - The platform must be affordable using off the shelf parts ;
- Ease of Maintenance - The platform should have low maintenance requirements and be easy to repair;
- Ease of Assembly - Reconfigurable platforms are required for multiple purposes so the reconfiguration should be easy and relatively quick;
- Low Weight - The platform should be easy to move to various fields as needed. It should also be easy for a person to lift and position once in the field.

In order to meet the above requirements, a multi-purpose mobile platform has been designed by selecting, evaluating and integrating several commercial off-the-shelf mechatronic components.

The platform has been designed to cope with typical field terrains and the final concept is composed of four integrated wheel drives and wheel steering sub-systems for reliable mobility. It uses four in-wheel motors to reduce the weight and the size. The platform is roughly 400 mm long, 400 mm wide and 254mm tall and weighs ~15.5kg (25kg full load) with hardware and batteries [12].

Instantaneous Power Modelling

Given the unstructured and unknown environments in which the *AgriRover* will operate, it is important to model power consumption to ensure the system meets the affordability and operational time requirements. A new method of measuring the energy efficiency of a mobile platform is proposed which can be applied to any mobile technology using legs or wheels. The dynamic energy efficiency of the *Agri-Rover* is derived in order to establish the key energy performance characteristics of the mobile platform. This will allow for the evaluation of the instantaneous and peak performance characteristics of the mobile platform in typical soil sensing operations. In these applications, it is insufficient to measure only the static energy efficiency and as such the new approach includes time analysis.

The instantaneous power is derived from first principles. Referring to Eqn. 1, the average power as the time interval Δt approaches zero is given by [13].

$$P = \lim_{\Delta t \to 0} P_{avg} = \lim_{\Delta t \to 0} \frac{\Delta W}{\Delta t} = \frac{\mathrm{d}W}{\mathrm{d}t} \qquad 1$$

P_T is the total power required at any instant while P_m is the power used for the displacement of the rover and is a value which will differ with different acceleration and P_s is the power used for steering the rover. To overcome the friction, which in

turn depends on the contact surface, P_f is introduced. The power associated with the heat loss of the propulsion system is expressed by P_h, which is proportional to the current that passes through the propulsion system. Finally, P_e is the power required for the on-board electronic equipment. Thus:

$$P_T = P_m + P_s + P_f + P_h + P_e \quad 1$$

where P_m is the sum of the power on each wheel, and at any given time:

$$P_m = F \cdot V_l \quad 3$$

P_s is the power consumed by the steering system, and it is calculated as:

$$P_s = \tau \cdot \omega \quad 4$$

The driving motors heat loss P_{hd} is a function of P_m and can be considered as the efficiency of the rover motor and the motor driver. It is calculated as:

$$P_{hd} = P_m \cdot (1 - \eta) \quad 5$$

The steering motors heat loss P_{hs} can be calculated as:

$$P_{hs} = P_s \cdot (1 - \eta) \quad 6$$

When P_h will be the sum of P_{hs} and P_{hd}.

At an instant the instantaneous power P(t) can be defined as:

$$P_{(t)} = \frac{dW}{dt} \quad 7$$

According to the total power required at any instant, the energy cost of the rover E_t can be defined by:

$$P_T = \int P \cdot dt \quad 8$$

Merging Eqn. 2 and Eqn. 8, in any given time interval from t_1 *to* t_2, the *AgriRover* energy consumption E_T is given by the integral:

$$P_T = \int_{t_1}^{t_2} (P_m + P_s + P_f + P_h + P_e) \cdot dt \quad 9$$

Applying Eqn. 9, it is proposed to define the Total Cost of Transport (TCoT) to be the ratio between the power consumption and the product of weight and velocity in real time, enhancing the static measurement introduced by Bhounsule *et al* [14] when:

$$\text{TCoT} = P_T(t)/(W(t)*V(t) \quad 10$$

where W and V are the weight of the *AgriRover* and the velocity at which it travels. Applying Eqn.10, it is possible to estimate the dynamic total cost of transport as shown in Fig. 3.

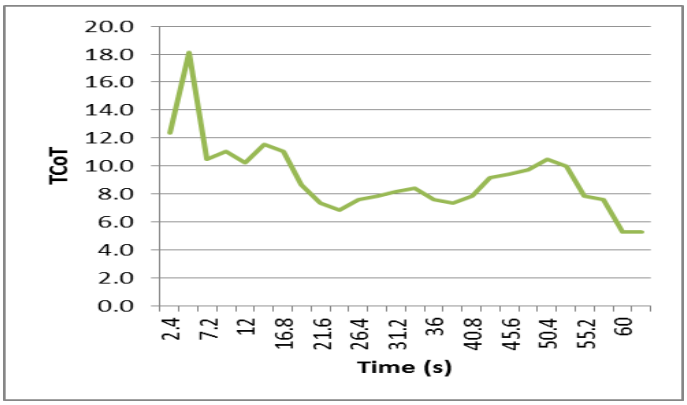


Fig. 3. A dynamic energy efficiency plot example at 30% of the maximum speed running for 18.3 meter and 63 seconds and with an average speed of 0.3 m/s

It is important for agricultural applications to have this measure as it gives a more precise and continuous measurement of cost of moving the *AgriRover* in an unstructured and unknown terrain for soil sampling. This can be used as a criterion to guide the motion planning discussed below.

Soil sample collection mechanism

The *AgriRover*-Sensing is equipped with a laser induced breakdown spectrometer (LIBS) system for soil sensing and detection of nitrogen. The design and operation of the LIBS system in analysing a soil sample can be found in Yan et al [15]. This paper focuses on the mechatronic aspect of the *AgriRover* system, i.e. how the sample will be collected and prepared ready for LIBS analysis.

Depth of soil sampling is the first issue to be addressed. For soil sampling for nitrogen measurement Miransari & Mackenzie [16] suggested a depth between 30 cm and 100 cm. Due to the limited payload weight of the *AgriRover*, it is important to keep the drill weight to a minimum, and deeper penetration will lead to longer and heavier sampling mechanisms. It has been therefore decided to set a depth of 50 cm based on the consultation with soil experts from the Chinese project partners. Renderings of the overall design are shown in Fig. 4.

(a) 

(b) 

Fig. 4. Mechatronic driller design. (a) Fully assembled *AgriRover* with soil sensing capability known as *AgriRover*-Sensing with (b) a soil sampling prototype

Agricultural Object Recognition

An agricultural objects recognition software module has been developed to enhance the autonomous navigation capabilities of the rover. The module recognises agricultural landmarks such as fences, trees and buildings taking as input the raw pixel images received by the on-board *Zed Camera*, and outputs an object membership class for each pixel.

The core pixel labelling work is executed by the Darwin framework [17], which operates as follows: (i) a preliminary classification of each pixel is computed by a machine learning algorithm, (ii) a segmentation algorithm decomposes the scene into compact regions, (iii) regions are classified according to a majority vote of the contained pixels, (iv) all the pixels in the regions are classified according to the majority vote.

A classification example of an agricultural object "*Cows*" is shown in Fig. 5. The left image is the original image. The right image is Darwin output. In the classification, a red colour refers to cows, the lighter blue colour refers to the sky, the darker blue colour refers to the ground, and the black colour represents unclassified areas.

Fig. 5. Agricultural object "*Cows"* recognition classification example

Autonomous Navigation and Task Planning

Navigation System Design

The *AgriRover* has been a validation platform for designing and testing an autonomous navigation system and experimenting with modern perceptual and decisional algorithms. The ambitious software architecture is depicted in Fig. 6. In this implementation, the rover is responsible for the collection and analysis of soil samples in a farm fields. When a user sends the terrestrial coordinates of the point of interests, the rover reaches the locations and performs the drilling and soil analysis tasks.

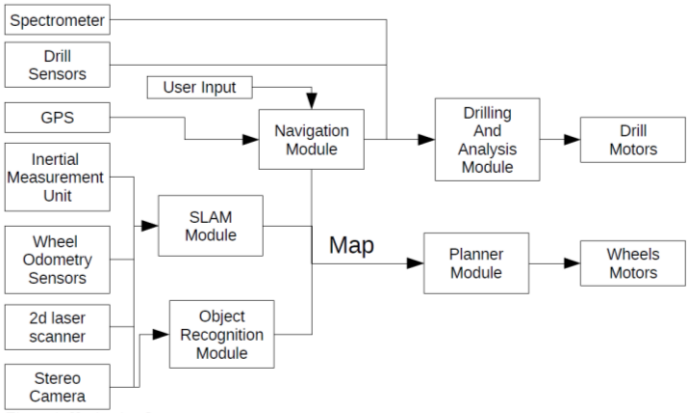


Fig. 6. *AgriRover* navigation system architecture

The navigation system relies on seven sources of information: (i) a pair of stereo cameras, (ii) a 2D laser scanner, (iii) an inertial measurement unit, (iv) the wheel odometry sensors, (v) a GPS, (vi) a drill movement sensor and (vii) the spectrometer for soil analysis. The rover performs its operations with two actuators, the wheel motors and the drill motors. The navigation system comprises five high level modules: (i) a SLAM module for localization and mapping, (ii) an object recognition module for obstacle detection, (iii) a planner module for path planning and movement execution, (iv) a navigation module for management of the locations of interest and (v) a drilling module for drilling and analysis of the soil samples.

The SLAM module uses the information from the cameras, the laser, the IMU and the wheel odometry, to produce a set of 3D points representing the space the rover visited and hence to determine the current position of the robot. The map and the position are constantly updated during movement, and allow the robot to maintain perception of its environment.

In the SLAM module, the implementation of RTAB-MAP in [18] available in the ROS public repository was used. The module performs a series of steps as follows:

(i) a point cloud is created for each pair of stereo images by triangulation; (ii) 2D features are extracted from the stereo images and features belonging to consecutive images are compared. Their relative displacement is then used to compute the distance the rover moved in the time interval between the two image recordings; (iii) consecutive laser scans are compared to obtain another estimation of the robot movement; (iv) different estimations of the robot movement are combined by means of a Kalman filter to obtain a final estimation; (v) point clouds are overlapped at the position predicted by the movement estimations and a complete point cloud produced; (vi) if the rover re-visits a location, then a loop closure occurs, the map is adjusted and the estimated positions are updated. Thanks to the loop closure step, re-visited locations are duplicated by virtue of the estimation errors.

The obstacle detection module analyses the 2D camera images and locates obstacles within the 3D map. This module uses the public implementation of the Darwin methodology [17], and performs pixel classification of an image, according to a pre-trained model as described above. Once pixels are classified, they are projected onto the 3D map by means of the same triangulation performed by RTAB-MAP. In the experiment, it was necessary to pre-train a model by providing a set of manually classified images to the Darwin learning algorithm.

The navigation module keeps information about the locations the rover visited and the locations the rover needs to visit. Whenever a new location needs to be reached, the navigation module passes the information to the planner module. Once the location is reached, the navigation module activates the drilling and soil sampling components.

The planning module computes a 2D movement path within the 2D projection of the reconstructed map, it also transforms the high level path plan into movement commands for the wheel actuators. This module uses the NAVFN [19] global path planner implementation available in the public ROS repository, in conjunction with a system specific implementation of a local path planner. It is essential for the planning stage that the rover correctly perceives its position inside the map at all time, in order to send timely correction commands to the wheel actuators if unwanted deviations are detected.

Energy Based Path planning

The *AgriRover* should complete its soil sampling task using the minimum amount of energy. For this reason, the total cost of transport (TCoT) is evaluated as a measure of energy efficiency. Table1 reports some values of the cost of transportation as measured during field trials with the *AgriRover*.

Table 1. Field trial preliminary results

Set Speed	Distance Travelled (m)	Time (s)	Average Speed (m/s)	TCoT

15.00%	37.1	58.0	0.64	4.67
30.00%	18.3	62.0	0.25	9.1
50.00%	20.0	43.0	0.46	7.91
100.00%	18.3	22.0	0.83	6.70

Table 1 shows that the speed, duration, distance travelled and average speed influence the rover's energy consumption. It is observed that the TCoT is lower either when the rover is at full speed or minimum speed. This indicates that it is beneficial to select the most appropriate speed at path planning time.

In addition, a good understanding of the field's three dimensional terrain is critical for planning an appropriate path, as moving uphill and downhill along the shortest path might be more energy expensive than a longer flat path. These insights inform the 3D planner presented below.

Energy optimization path planning

For a transfer task, a further distance needs to be travelled by the rover, as for instance when the rover needs to relocate to a nearby field or when the rover needs to go to a charging station. Energy can be wasted if conventional path planning methods are deployed, so an energy optimization path planning algorithm is used.

This algorithm is based on artificial potential fields with enhancement [20] with environment and rover property variables used as input. For each factor that influences the energy consumption, an artificial potential field map is calculated. All such a potential field maps are then combined and the distance potential field calculated based on the terrain map. Suppose X and Y are the horizontal and vertical coordinates for a given point and X_d and Y_d the horizontal and vertical coordinates for the destination point and G is gravity, then the distance potential field E_P is calculated as follows:

$$E_P = G\sqrt{(X - X_d)^2 + (Y - Y_d)^2} \quad 11$$

The potential field of height difference is calculated on the basis of the topographic map and the formula for elastic potential energy. Suppose H_P is the starting point height and H_D is the destination point height, then, a potential field for height difference E_p is calculated as follows:

$$E_P = \frac{1}{2}|H_P - H_D|^2 \quad 12$$

The two generated potential fields are combined as the weighted sum of the potential fields with each potential field having an adjustment factor based on its importance. Based on the final combined potential field, a path finding algorithm is used to find the path for the rover by simulating a free rolling ball from a high potential energy point to a lower point. An evaluation algorithm is utilized to assess

how long the path is, how long the vertical component of the path is and if there is any collisions with the obstacle.

In the study, the original point is located on the top left and the destination point on the bottom right has been set and two paths have been found as shown in Fig. 7. In Fig. 7(a) a path found using conventional path planning and in Fig. 7(b) a path is identified by deploying energy optimized path planning.

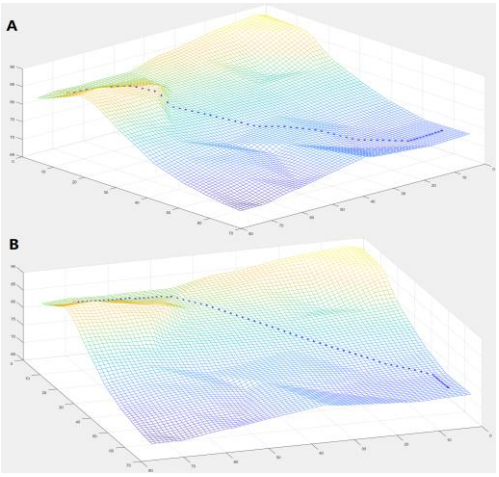


Fig. 7. Path found by (a) straight path planning and (b) the energy optimized path planning

The height and position relationship diagrams of these two paths can now be generated, as shown in Fig. 8. Based on this figure, the energy needed to overcome gravity is calculated with equation W = mgh (m is the mass of rover, *g* is gravity and *h* is height). Here, the weight of the rover is 25-kg and the rolling resistance coefficient is 0.15. In straight path planning, the energy cost to overcome gravity is 406.7 joules. In optimized path planning, the energy cost to overcome gravity is 90.65 joules. As shown in the simulations, most of the uphill terrain can be avoided and energy saved with optimized path planning.

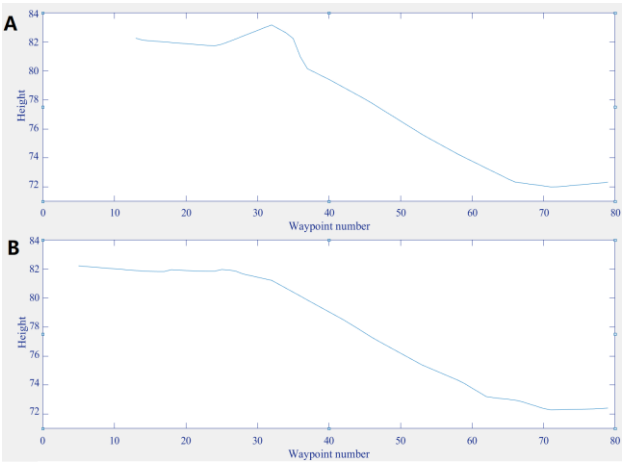


Fig. 8. Diagram of height-position relationship for straight path (A) and energy optimized path (B).

Discussion and Future Work

Reinvention

New industrial demands pose challenges to traditional mechatronic approaches and their associated systems. This chapter addressed such challenges from an agricultural context, and proposes a reinvention approach:

- New emerging technologies allow mechatronics professionals to contribute to the agriculture either through reinvention or incremental improvement.
- Research in space robotics have produced several technologies applicable on Earth, such as autonomous navigation, soil chemical composition measurement, and a sample drilling and collection mechanism. All these technologies can offer inspiration for mechatronics reinvention.

Future mechatronic research directions

This study attempts to use machine learning to train and create a capability to recognise agricultural objects. The number and types of the agricultural objects investigated within the project to date are limited and these will be extended to make the *AgriRover* system more applicable for wider crops and fields.

In order to ensure the correctness of the detected obstacles within the map and allow the navigation algorithm to compute correctly the path to the destination, a map refinement system will be added. In addition, a terrain detection module will be investigated and added to the object detection module in order to allow the robot to choose the best image sampling strategy, and the best odometry correction procedure.

Amore energy efficient path planning and operation control system will be investigated in order to address the battery capacity challenge which is constrained by the overall weight from the design specifications.

Conclusions

The *AgriRover* system demonstrated a new way of tackling the soil quality measurement challenge faced globally through a mechatronic reinvention design process. The reinvented mechatronic solution *AgriRover* represents a holistic step forward in addressing agricultural soil measurement and management, and selective harvesting. This has shown a new technology to support sustainable, cost-effective and real-time soil quality measurement for future farming. The *AgriRover* has already generated societal impact and been defined as a key technology for a future SmartFarm project, a flagship challenge project in AgriTech collaboratively investigated by the researchers from the UK and China. It is believed by researchers that the *AgriRover* will provide farms with new technologies to enhance farm productivity, whilst maintaining environmental sustainability, by providing much needed reliable and timely soil fertility information.

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