Adaptive Surveying and Early Treatment of Crops with a Team of Autonomous Vehicles

Kazmi, Wajahat; Bisgaard, Morten; Garcia-Ruiz, Francisco ; Hansen, Karl Damkjær; la Cour-Harbo, Anders

Published in:
Proceedings of the 5th European Conference on Mobile Robots ECMR 2011

Publication date:
2011

Document Version
Accepted author manuscript, peer reviewed version

Adaptive Surveying and Early Treatment of Crops with a Team of Autonomous Vehicles

Wajahat Kazmi* Morten Bisgaard‡ Francisco Garcia-Ruiz† Karl D. Hansen‡ Anders la Cour-Harbo‡
*Department of Architecture, Design and Media Technology, Aalborg University, Aalborg-9220, Denmark
†Department of Agriculture and Ecology, University of Copenhagen, Taastrup-2630, Denmark
‡Department of Electronics Systems, Aalborg University, Aalborg-9220, Denmark

***Abstract*— The ASETA project (acronym for Adaptive Surveying and Early treatment of crops with a Team of Autonomous vehicles) is a multi-disciplinary project combining cooperating airborne and ground-based vehicles with advanced sensors and automated analysis to implement a smart treatment of weeds in agricultural fields. The purpose is to control and reduce the amount of herbicides, consumed energy and vehicle emissions in the weed detection and treatment process, thus reducing the environmental impact. The project addresses this issue through a closed loop cooperation among a team of unmanned aircraft system (UAS) and unmanned ground vehicles (UGV) with advanced vision sensors for 3D and multispectral imaging. This paper presents the scientific and technological challenges in the project, which include multivehicle estimation and guidance, heterogeneous multi-agent systems, task generation and allocation, remote sensing and 3D computer vision.**

***Index Terms*— multivehicle cooperation, multispectral imaging, precision farming, 3D computer vision.**

I. Introduction

Weeds have always remained a major concern to farmers because they compete with crops for sunlight, water and nutrients. If not controlled, they can cause a potential loss to the monetary production value exceeding a global average of 34% [1].

Classical methods for weed removal are manual or mechanical which are time consuming and expensive. Over the last few decades, herbicide application has been a dominant practice. Indiscriminate use of chemicals, on the other hand, is also detrimental to both environment and the crop itself.

Reduction in the use of pesticides in farming to an economically and ecologically acceptable level is one of the major challenges of not just developed countries but also the developing countries of the world. Introducing an upper threshold to the amount of pesticides used does not necessarily serve the purpose. It must be accompanied with the knowledge of when and where to apply them. This is known as Site-Specific Weed Management (SSWM). For SSWM, the concept of precision farming scales down to field spots or patches [2] or even to plant scale [3]. This requires real-time intelligence on crop parameters which significantly increases the complexity of modern production systems and therefore imply the use of automation through information technologies, smart sensors and decision support systems.

Over the last five decades, the concept of agricultural automation has evolved from mechanization of manual labor into intelligent sensor based fully autonomous precision farming systems. It started with automation of ground vehicles [4] and over time, air vehicles also found their way in. Furthermore, advanced perception technologies such as machine vision have become an important part of agricultural automation and 2D/3D image analysis and multispectral imaging have been very well researched in agriculture.

Today, with advanced sensor technologies and both air and ground, manned and unmanned vehicles available in the market, each one with its own pros and cons, the choice has become broad. The technology is at par with most of the industrial demands but the need is of an optimal subset of technical attributes since the practice, particularly in agriculture, has usually been limited to the use of one type of vehicle with a limited sensor suite. The drawback of this scheme is that one type of vehicle is unable to satisfy all operational requirements. For example an unmanned aircraft (UA) to detect and apply spray to the aquatic weeds compromises on spray volume, precision and duration of flight due to weight-size constraints [5], while a ground vehicle alone can significantly slow down the operation along with producing substantial soil impact [6], not to mention the problem of emissions.

These constraints imply the use of a team of both air and ground vehicles for a holistic solution. Unmanned (ground) vehicles being considerably smaller in size than manned vehicles have lesser soil impact and fuel consumption (thus have reduced emissions) and may also be battery operated. Therefore, for economy of time and energy and for higher precision, a network of unmanned air and ground vehicles is inevitable and is destined to outperform conventional systems. Research has also been conducted in cooperative unmanned mixed robotic systems both for civil and military purposes, for example, [7] proposes hierarchial framework for a mixed team of UAS and UGV for wildfire fighting and GRASP laboratory [8] used such systems in urban environments as a part of MARS2020 project. But apparently, no such strategy has been adopted in agriculture. To the best of authors' knowledge, ASETA is the first project of its kind to use a team of both UAS and UGV in agriculture which has opened a new chapter in precision farming and researchers especially in the European Union are taking increased interest in such approaches (for example, RHEA project [9]).

This paper describes the scope of ASETA's scientific research, its heterogeneous robotic fleet and sensor suite for SSWM. The paper is organized as follows: the project is described in section II, followed by equipment summary in

W Kazmi, M Bisgaard, F. Garcia-Ruiz, K.D. Hansen, and A. la CourHarbo. Adaptive Surveying and Early Treatment of Crops with a Team of Autonomous Vehicles. In European Conference on Mobile Robots, pp: 253 – 258, Orebro, Sweden, 2011.

section III. Main research areas of this project in the context of the related work are presented in section IV. Section V concludes the paper.

II. ASETA

ASETA (Adaptive Surveying and Early treatment of crops with a Team of Autonomous vehicles) is funded through a grant of 2 million EUR by the Danish Council of Strategic Research. It aims at developing new methods for automating the process of acquiring and using information about weed infestation for an early and targeted treatment. The project is based on the following four hypotheses:

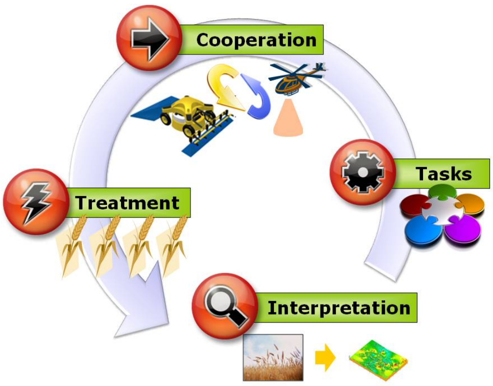

Fig. 1. ASETA Strategy

1) Localized detection and treatment for weeds will significantly decrease the need for herbicides and fuel and thereby reduce environmental impact.
2) Such early detection can be accomplished by multi-scale sensing of the crop fields by having UAS surveying the field and then performing closer inspection of detected anomalies.
3) A team of UAS and UGV can be guided to make close-to-crop measurements and to apply targeted treatment on infested areas.
4) A team of relatively few vehicles can be made to perform high level tasks through close cooperation and thereby achieve what no one vehicle can accomplish alone.

The strategy adopted in ASETA (Fig. 1) is to survey crop fields using UAS in order to obtain and localize hotspots (infested areas) through multispectral imaging followed by cooperative team action among a team of air and ground vehicles for a closer 3D visual inspection, leading to the treatment. Survey may be iterated depending on the team size and field dimensions.

Obviously, ASETA's industrial gains come at the cost of certain technical and scientific challenges. A heterogeneous team of several unmanned vehicles is chosen to distribute heavy payloads on ground vehicles (sensing, perception and treatment) and relatively lighter payload (sensing and perception only) on the air vehicles which potentially is a well balanced approach but puts high demands on team cooperation and task management keeping in view the constraints of each team member. A further complexity to the proposed system arises from the fact that although computer vision is very popular and successful in plant inspection, however, changing weather and sunlight conditions has so far limited in-field agricultural vision systems [10]. These challenges must be addressed in order to produce an optimal combination of more than one type of unmanned vehicles to outperform the conventional systems in the scope. Therefore, in order to achieve its goals, ASETA will carry forward scientific research in four directions, namely, multispectral imaging, 3D computer vision, task management and multivehicle cooperation.

The project started in January 2010. Major research work will be carried out from 2011 to 2013. Scientific research is being conducted by four post graduates and several faculty staff involved at two Danish universities, University of Copenhagen and Aalborg University. This collaborative work is a mixture of theory, simulations, and actual fields tests. The latter is done in cooperation with the university farms at University of Copenhagen, which will maintain a field of sugar beets throughout the growth seasons in 2011 to 2014. Since sugar beet is the crop-of-choice for the demonstrative part, Nordic Beet Research is also involved in the project.

III. Equipment

Some of the specialized equipment used in this project is described below:

A. Robotic Platforms

ASETA has three unmanned mobile robots available for the project. They are briefly described below:

1) UAS: The UAS is comprised of two rotary wing aircraft. The first UA is a modified Vario XLC helicopter with a JetCat SPTH-5 turbine engine (Fig. 2). The helicopter weighs 26 kg when fully equipped for autonomous flight and can fly for 30 minutes with 6 kg of fuel and 7 kg of payload. For autonomous flight, a NAV440 Inertial Navigation System (INS) from Crossbow is used together with altitude sonar. Onboard computer is a Mini-ITX with dual-core 1.6 GHz Intel Atom processor and runs a Debian Linux operating system. The flight time in this configuration is approximately 30 minutes.

The second UA is a modified Maxi Joker-3 helicopter from MiniCopter. It is electrically powered and weighs 11 kg when equipped for autonomous flight (Fig. 2). The helicopter can fly for 15 minutes with a payload of 3 kg. It has a Xsens MTiG INS and sonar altimeters for autonomous flight and Nano-ITX size 1.3 GHz onboard computer with Debian Linux operating system.

Each UA can be configured to carry the multispectral camera (see Section III-B) or a color camera. The sensors are mounted in a modified OTUS L205 gimbal from DST Control. The low level guidance, navigation, and control (GNC) system for the UAS is the baseline GNC software from Aalborg University's UAV lab[1]. It features gain scheduled optimal controller, unscented Kalman filter for navigation and an advanced trajectory generator.

[1] www.uavlab.org

Fig. 2. Autonomous vehicles in ASETA, (from left): Vario XLC, Maxi Joker-3 and robuROC-4

2) UGV: The ground vehicle is a robuROC-4 from Robosoft (Fig. 2). Running on electric power this vehicle is designed for in-field use and will carry the TOF (see Section III-B) and color cameras for close-to-crop inspection. The total weight is 140 kg (without vision system) and it is controlled by a standard laptop residing under the top lid running the cross-platform robot device interface Player/Stage. This vehicle is equipped with RTK GPS to allow it to traverse the crop rows with sufficient accuracy.

B. Vision Systems

As described in section II, two different imaging systems will be used: one for remote sensing and another for the ground based close-to-crop imaging. For remote sensing, a multispectral camera will be employed and for ground based imaging a fusion of Time-of-Flight and color images will be explored.

1) Multispectral Camera: The multispectral camera used in the project is a Mini MCA from Tetracam[2] (Fig. 3). This specific sensor weighs 695 g and consists of six digital cameras arranged in an array. Each of the cameras is equipped with a 1.3 megapixel CMOS sensor with individual band pass filters. The spectrometer filters used in this project are 488, 550, 610, 675, 780 and 940 nm (bandwidths of 10 nm). The camera is controlled from the on-board computer through an RS232 connection and images are retrieved through a USB interface. Video output is also possible using the output video signal in the control connector.

Fig. 3. Mini MCA multispectral camera.

2) Time-of-Flight Camera: A time-of-flight (TOF) camera system has the advantage that depth information in a complete scene is captured with a single shot, thus taking care of correspondence problem of stereo matching. In this project, Mesa Imaging's $SwissRanger^{TM} SR4000$ [3] USB camera will be used which is an industrial grade TOF camera allowing high quality measurements in demanding environments. It operates in the Near-InfraRed (NIR) band (illumination wavelength 850 nm) hence a stable measurement accuracy and repeatability can be achieved even under variations in object reflectivity and color characteristics. SR4000 can deliver a maximum frame rate of 50 frames/sec. As usually is the case with TOF cameras, the resolution is fairly low (176 x 144 pixels) which will be augmented by fusion with high resolution color images.

Fig. 4. SwissRanger SR4000 TOF Camera

IV. Research Areas

The main scientific contributions will be generated by four research positions associated with the ASETA loop (Fig. 1). Two PhD studies in analysis and interpretation of images detection and treatment of weeds and one PhD study and one Post Doc in task allocation and vehicle cooperation. They are briefly described below in the context of the state-of-the-art.

A. Multispectral Aerial Imaging for Weed Detection

As already discussed in section I, SSWM involves spraying weed patches according to weed species and densities in order to minimize herbicide use. However, a common approach in SSWM is weed mapping in crops which is still one of the major challenges. Remote sensing supplemented by targeted ground-based measurements have been widely used for mapping soil and crop conditions [11, 12]. Multispectral imaging at low and high spatial resolution (such as satellite and airborne) provide data for field survey and weed patch allocation but depending on the system used, it varies in accuracy [13].

A higher level of spectral difference between plant and soil makes their separation relatively easy in a multispectral image.

[2]www.tetracam.com

[3]www.mesa-imaging.ch

But the spectral ambiguity among plant species makes plant classification a difficult task. Thus, the spatial resolution of the sensor becomes an essential criterion for a reliable vegetation discrimination in order to detect the spectral reflectance in least altered form to avoid spectral mixing at pixel level [14]. Therefore, the major requirements for robust aerial remote sensing for weed identification are a high spectral resolution with narrow spectral bands and the highest possible spatial resolution (normally limited by sensor technology) [15].

The high usability of multispectral satellite imagery from *QuickBird* (2.4 to 2.8 meter spatial resolution) in a sugar beet field for *Cirsium arvense* L. hotspot detection for a site-specific weed control having spot diameters higher than 0.7 m was demonstrated by [16]. The relatively low spatial resolution along with the inability to image ground during cloudy conditions make such systems less suitable for analyzing in-field spatial variability. On the other hand, high resolution images (up to 0.707 mm/pixel) were acquired in a rice crop for yield estimation using a UA flying at 20 m [12].

Keeping this fact in view, in this project, the choice of camera equipped unmanned helicopters is made because they can be guided at lower altitudes above the crop canopy in contrast to the satellite and manned airborne systems, increasing image resolution and reducing atmospheric effects on thermal images [17, 18]. Images obtained from low altitudes will support accurate decision making for precision weed and pest management of arable, tree and row crops.

The goal of aerial imaging in ASETA is to explore the potential of multispectral imaging involving multistage sampling for target detection meanwhile employing spatial sampling techniques (stereology) for real-time density estimation. Stereology will be used for target sampling at various scales, using information from lower resolution images (high altitude-helicopter) to plant measurements at higher resolutions (low altitude-helicopter) to maximize information from sparse samples in real-time while obeying rules of probability sampling [19]. The maps of the field provide the basis for optimal designs of sampling locations over several spatial scales using variance reduction techniques [19].

B. 3D Computer Vision for Weed Detection

Multispectral aerial imaging will be able to detect hotspot locations and volumes, but on a macro level. It cannot resolve individual plants at intra-row level. A ground based imaging system will thus be employed for close-to-crop inspection in this project.

In agricultural automation, the expected outputs of a weed detection system are weed plant detection, classification and stem center localization. Ground based imaging is not new but research has mainly focused on weeds at very early growth stages. There are two main reasons for this; an early detection will lead to an early treatment and the fact that plant imaging and recognition is one of the most demanding tests of computer vision due to complicated plant structures and the occlusion of crop and weed plants at later stages of growth prevents the proper visual separation of individual plants. While some efforts have shown promise under conditioned environments such as green houses, lack of robust resolution of occlusions remains a major challenge for in-field systems [20]. By utilizing 3D visual information it becomes possible to detect occlusions and make a better visual separation. Keeping this fact in view, the major objective in this project in ground based imaging is to utilize 3D computer vision techniques in weed detection.

There has been a significant amount of research work done towards 3D analysis of plants as well, but again this has mainly been aimed at navigation in the field, in estimating overall canopy properties through stereovision or creating very detailed models of plants [10]. 3D modeling is computationally expensive and is potentially hampered by thin structures, surface discontinuities and lack of distinct object points such as corners ending up in the correspondence problem [21]. These limitations pose a major challenge for in-field real-time 3D analysis of plants.

In order to address these problems, active sensing system based on Time-of-Flight (TOF) technology will be used which has been very scantily tested in agricultural applications mainly due to a very high sensor cost. TOF has a drawback of low resolution and sensitivity to ambient light, but these problems have been recently addressed and having TOF depth map fused with high resolution color image has shown very encouraging results especially with parallelized computations which significantly reduces the runtime [22]. The idea, therefore, is to use TOF data integrated with high resolution color images to perform in-field plant analysis. TOF technology has only recently found its way towards industrial applications and in agricultural automation its utility assessment is quite fresh [23, 24, 25].

While 3D analysis is required for resolving occlusions and localization of plant body, discrimination of weeds from crops is still another challenge. Pattern and Object Recognition techniques have been widely used in weed discrimination [26]. But most of the techniques use color or size of the leaves (Leaf Area Index-LAI) as prime feature. The size of the leaves or the exposed area of the leaves vary due to orientation, growth stage and weather conditions. Furthermore, variations in the soil conditions and the amount of sunlight can result in color variations. Instead, vision systems based on shape are less sensitive to variation in target object color [10]. In this project, a shape based approach in distinguishing sugar beet crop plants from weeds will be used, for example [27].

In general, ASETA will contribute a new approach in weed identification by combining TOF technology with pattern recognition techniques bringing the lab research to the field.

C. Task Management

The idea of Future Farms is that the farm manager should be able to–more or less–just press a button, and then leave it until the process is finished. This demands that the system is capable of identifying the subtasks contained in this high-level command and ensure their execution. These two processes are commonly known as *Task Decomposition* and *Task Allocation*.

The task decomposition process is going to break down the overall task to small manageable chunks, that the individual members (robots) of the system are able to execute. The decomposition depends on the combined set of capabilities of the members. For example, if a member has the capability to take very high resolution images, the initial images might be taken from high altitude and only a few overview images may be sufficient for mapping the the entire field. Whereas, if only low resolution cameras are available, several overview images may be required.

When the overall task has been decomposed into suitable subtasks, they must be distributed to each of the members in the system. This is known as Task Allocation. Several different approaches to this have been investigated. Two broad categories can be identified as centralized and distributed allocation. The centralized approach is essentially a matter of solving a multiple travelling salesman problem (m-TSP). The distributed approach will divide the task of solving the TSP between each member. In this case the members must communicate with each other to make sure that two members are not planning to visit the same point (see section IV-D).

The TSP solution has historically received a great deal of attention and has shown to be $\mathcal{NP}$-hard [28], thus simple brute-force algorithms will not be practically usable in the system. The Lin-Kernighan heuristic [29] of 1971 is still one of the most preferred algorithms for solving TSPs, and maintains the world record of solving the largest TSP [30]. A strategy to solve the TSP with timing constraints (TCTSP) is devised in [31]. Helicopters conducting a closer examination of the weed infestations in the ASETA scheme will experience a TCTSP as the high altitude images will be taken over time and thus the close-up tasks are time constrained. Walshaw proposed a multi-level approach for solving the TSP [32]. This is relevant as the high altitude-helicopter process coarsens the TSP for the low altitude-helicopter, and thus gives a coarse representation of the low-level TSP free of charge.

The decentralized approach relies on the members to distribute the tasks among themselves, without intervention of a governing system. The MURDOCH allocation system uses an auctioning approach where each robot bids on the different tasks depending on their own perceived fitness for the task at hand [33]. The fitness assessment of the ALLIANCE architecture [34] is based on a impatience behavioral pattern. These approaches will not guarantee the optimal solution, but provide some robustness that might be missing in the centralized approach.

The aim of the ASETA task management is to utilize existing TSP solving methods such as Lin-Kernighan or Walshaw approach and adapt them to the situation at hand, with the members gradually revealing more and more information as they move closer to the crops, from the high altitude- over to the low altitude-helicopter down to the ground vehicle.

D. Multivehicle Cooperation

The close cooperation among team members (robots) is an important part of ASETA in order to ensure a safe and efficient execution of the tasks provided by the Task Management. The cooperation layer will determine which robot will tackle which task and to some extent in what order. In a situation where a team of heterogeneous robots must cooperate in order to complete a task in an open-ended environment, it is crucial that each member has a clear understanding of its own as well as the other members' capabilities because they are not equally qualified to handle a given task. In this project, The helicopters are equipped with several different types of sensors including cameras (as described in section III) well suited for observation only and the ground vehicle has an altogether different sensor suite and is meant for closer inspection and treatment. This information is to be used by every member to decide which part of the overall task it should handle and how to do it.

To ensure a timely and efficient execution of the tasks it is equally important for a robot to know what its team members are doing – i.e. their behavior – and thereby ensuring that two members do not unnecessarily work on the same subtask. However, it is not always trivial to acquire such knowledge. The distances involved in field operations can potentially become very large and thus can only allow limited communication. Furthermore, when reducing necessary communication among members, backwards compatibility is made easier and this is preferable in a industrial product. Therefore, the members must be able to deduce this knowledge from very limited information such as the state (position, orientation, and velocity) of the other members. This will put lesser constraints on the robots that are allowed to participate in the cooperation. In fact even robots without any cooperative capabilities can be a part of the system, as long as they can share their state with the rest of the team.

Current research in cooperative control of multivehicle systems focuses mainly on the control element such as formation control or distributed optimization. A comprehensive review of recent research in cooperative control can be found in [35]. Only few projects have taken the limited communication between robots into account (for example: [36] or [37]).

In this project, the actual cooperation layer is created as a decentralized two-level approach:

1) Level 1: Acquiring team behavioral information: The challenges of this level are seen primarily as a model based estimation problem which will be solved using particle filtering. This is done through the formulation of a behavioral modeling framework which in turn describes the different possible behaviors of the members. When used in a particle filter, it is capable of determining the maximum likelihood hypothesis, i.e. best fitting behavior of the observed team members.

2) Level 2: Task execution: Each member is assumed to be containing a low level navigation and control system as well as simple trajectory planning. As a high level control, a receding horizon is used in the form of a decentralized Model Predictive Controller (MPC). The MPC on each member will attempt to find an optimal behavioral action to take, given information about the current behavior of the rest of the team.

In short, the ASETA cooperation scheme will use particle filtering and model predictive control to implement cooperation between loosely coupled robots.

V. Conclusion

ASETA will not only produce high quality research in multispectral imaging, computer vision and multivehicle systems, but it also aims at developing an actual demonstrator. Working within the price range of other farming machinery and the use of off-the-shelf hardware throughout enhances the likelihood of tools developed in this project being adopted by the industry. The long term objective of ASETA is a commercially available autonomous multi-scale surveying system for site specific weed management to reduce the cost and environmental impact of farming chemicals, fuel consumption and emissions. It therefore holds the potential for significant impact on the future of precision farming worldwide.

Given the rising levels of atmospheric CO_2 and temperatures under climate change, weed species are expected to show a higher growth pattern than crops due to their greater genetic diversity [38]. On the other hand, governments mandate considerable reductions on the use of pesticides. This fact has added more importance and promise to such projects.

Although dealing with a system of heterogeneous vehicles increases the complexity of the system, however, it also serves as a flexibility on the user end in the choice of vehicles and sensors from a wide range, producing a more customized solution to the application at hand. ASETA, therefore, has future beyond agriculture towards several other applications such as fire fighting, search & rescue and geological surveying, in the long run.

References

[1] E. Oerke, "Crop losses to pests," *The Journal of Agricultural Science*, vol. 144, no. 01, pp. 31–43, 2006.

[2] S. Christensen, T. Heisel, A. M. Walter, and E. Graglia, "A decision algorithm for patch spraying," *Weed Research*, vol. 43, no. 4, pp. 276–284, 2003.

[3] M. Ehsani, S. Upadhyaya, and M. Mattson, "Seed location mapping using RTK GPS," *Trans.-American Society of Agricultural Engineers*, vol. 47, no. 3, pp. 909–914, 2004.

[4] K. Morgan, "A step towards an automatic tractor," *Farm mech*, vol. 13, no. 10, pp. 440–441, 1958.

[5] A. H. Göktoğan, S. Sukkarieh, M. Bryson, J. Randle, T. Lupton, and C. Hung, "A rotary-wing unmanned air vehicle for aquatic weed surveillance and management," *J. Intell. Robotics Syst.*, vol. 57, pp. 467–484, January 2010.

[6] V. Rusanov, "Effects of wheel and track traffic on the soil and on crop growth and yield," *Soil and Tillage Research*, vol. 19, no. 2-3, pp. 131 – 143, 1991.

[7] C. Phan and H. H. Liu, "A cooperative UAV/UGV platform for wildfire detection and fighting," in *2008 Asia Simulation Conference - 7th International Conference on System Simulation and Scientific Computing*, (Beijing), pp. 494–498, Ieee, Oct. 2008.

[8] L. Chaimowicz, A. Cowley, D. Gomez-Ibanez, B. Grocholsky, M. Hsieh, H. Hsu, J. Keller, V. Kumar, R. Swaminathan, and C. Taylor, *Deploying air-ground multi-robot teams in urban environments*, vol. III, pp. 223–234. Springer, 2005.

[9] "RHEA: Robot Fleets for Highly Effective Agriculture and Forestry Management," *http://www.rhea-project.eu/*, accessed 08-Apr-2011.

[10] C. L. McCarthy, N. H. Hancock, and S. R. Raine, "Applied machine vision of plants: a review with implications for field deployment in automated farming operations," *Intelligent Service Robotics*, vol. 3, pp. 209–217, Aug. 2010.

[11] K. R. Thorp and L. F. Tian, "A review on remote sensing of weeds in agriculture," *Precision Agriculture*, vol. 5, no. 5, pp. 477–508, 2004.

[12] K. C. Swain, S. J. Thomson, and H. P. W. Jayasuriya, "Adoption of an unmanned helicopter for low-altitude remote sensing to estimate yield and total biomass of a rice crop," *Trans. of the ASABE*, vol. 53, pp. 21–27, Jan-Feb 2010.

[13] M. S. Moran, Y. Inoue, and E. M. Barnes, "Opportunities and limitations for image-based remote sensing in precision crop management," *Remote Sensing of Environment*, vol. 61, pp. 319–346, Sep 1997.

[14] D. W. Lamb and R. B. Brown, "Remote-sensing and mapping of weeds in crops," *Journal of Agricultural Engineering Research*, vol. 78, pp. 117–125, Feb 2001.

[15] R. B. Brown and S. D. Noble, "Site-specific weed management: sensing requirements - what do we need to see?," *Weed Science*, vol. 53, pp. 252–258, Mar-Apr 2005.

[16] M. Beckes and J. Jacobi, "Classification of weed patches in quickbird images: Verification by ground truth data," *EARSeL eProceedings*, vol. 5(2), pp. 173–179, 2006.

[17] J. A. J. Berni, P. J. Zarco-Tejada, L. Suarez, and E. Fereres, "Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, pp. 722–738, Mar 2009.

[18] R. Sugiura, N. Noguchi, and K. Ishii, "Remote-sensing technology for vegetation monitoring using an unmanned helicopter," *Biosystems Engineering*, vol. 90, pp. 369–379, Apr 2005.

[19] D. Wulfsohn, "Sampling techniques for plants and soil: In. advanced engineering systems for specialty crops: A review of precision agriculture for water, chemical, and nutrient application, and yield monitoring.," *Landbauforschung Völkenrode*, vol. Special Issue 340, pp. 3–30, 2010.

[20] D. Slaughter, D. Giles, and D. Downey, "Autonomous robotic weed control systems: A review," *Computers and Electronics in Agriculture*, vol. 61, pp. 63–78, Apr. 2008.

[21] a. Piron, F. Van Der Heijden, and M. Destain, "Weed detection in 3D images," *Precision Agriculture*, pp. 1–16, Nov. 2010.

[22] B. Huhle, T. Schairer, P. Jenke, and W. Straßer, "Fusion of range and color images for denoising and resolution enhancement with a non-local filter," *Comp. Vision and Image Understanding*, vol. 114, pp. 1336–1345, Dec. 2010.

[23] G. Alenya, B. Dellen, and C. Torras, "3D modelling of leaves from color and ToF data for robotized plant measuring," in *Proc. of the International Conference on Robotics and Automation*, (accepted), 2011.

[24] M. Kraft, N. Regina, S. a. D. Freitas, and A. Munack, "Test of a 3D Time of Flight Camera for Shape Measurements of Plants," in *CIGR Workshop on Image Analysis in Agriculture*, no. August, (Budapest), 2010.

[25] A. Nakarmi and L. Tang, "Inter-plant Spacing Sensing at Early Growth Stages Using a Time-of-Flight of Light Based 3D Vision Sensor," in *ASABE Meeting Presentation*, no. 1009216, 2010.

[26] M. Weis and M. Sökefeld, *Detection and Identification of Weeds*, ch. 8, pp. 119–134. Dordrecht: Springer Netherlands, 2010.

[27] M. Persson and B. Åstrand, "Classification of crops and weeds extracted by active shape models," *Biosys. Eng.*, vol. 100, pp. 484–497, Aug. 2008.

[28] M. R. Garey and D. S. Johnson, *Computers and Intractability*. W. H. Freeman and Co., 1979.

[29] S. Lin and B. Kernighan, "An effective heuristic algorithm for the traveling-salesman problem," *Operations research*, vol. 21, no. 2, pp. 498–516, 1973.

[30] K. Helsgaun, "General k-opt submoves for the Lin-Kernighan TSP heuristic," *Mathematical Programming Computation*, vol. 1, pp. 119–163, July 2009.

[31] E. K. Baker, "An exact algorithm for the time-constrained traveling salesman problem," *Operations Res.*, vol. 31, pp. 938–945, Apr. 1983.

[32] C. Walshaw, "A multilevel approach to the travelling salesman problem," *Operations Research*, vol. 50, pp. 862–877, Sept. 2002.

[33] B. P. Gerkey and M. J. Mataric, "Sold!: auction methods for multirobot coordination," *IEEE Transactions on Robotics and Automation*, vol. 18, pp. 758–768, Oct. 2002.

[34] L. E. Parker, "Alliance: An architecture for fault tolerant, cooperative control of heterogeneous mobile robots," in *Proc. IROS*, pp. 776–783, 1994.

[35] R. M. Murray, "Recent Research in Cooperative Control of Multivehicle Systems," *Journal of Dynamic Systems, Measurement, and Control*, vol. 129, no. 5, pp. 571–583, 2007.

[36] G. M. Hoffmann, S. L. Wasl, and C. J. Tomlin, "Distributed cooperative search using information-theoretic costs for particle filters with quadrotor applications," in *Proceedings of the AIAA Guidance, Navigation, and Control Conference*, pp. 21–24, 2006.

[37] K. S. Alessandro Arsie and E. Frazzoli, "Efficient Routing Algorithms for Multiple Vehicles With no Explicit Communications," *IEEE Transactions on Automatic Control*, vol. 54, no. 10, pp. 2302–2317, 2009.

[38] L. Ziska and G. Runion, *Future weed, pest and disease problems for plants*, pp. 261–287. Boca Raton FL: CRC Press, 2007.