White paper

An Approach to Agricultural Robotics for Small and Family Farms

Damian M. Lyons, Mohamed Rahouti
Fordham University
Robotics and Computer Vision Lab.

Motivation: It is estimated that the world population will increase from 7.8 billion in 2020 by over 24% to 9.7 billion people in 2050 [21], and it is a global challenge to keep food production pacing this growth. Agricultural robotics has been put forward as a way to address seasonal shortages in labor, quality of fresh produce, lower production costs, enable more environmentally friendly practices, and reduce drudgery [17, 19, 15, 10, 4, 4, 23]. Robotic systems have been proposed for fruit picking [30], harvesting lettuce [6], identifying areas of weeds [7], automated tractor steering for tillage and planting [5], moving materials [20] and others [4, 3].

A popular approach to the challenge of robotic agriculture is to leverage "Precision Agriculture" [19]: Gathering and analyzing spatial and temporal data, often satellite imagery [31], to target actions that improve agricultural productivity. This approach is similar in inspiration to the way robots are traditionally used in manufacturing – structured spatial organization and assembly line processing. This lends itself well to large agribusiness and to monoculture farming – that is, specializing in producing large quantities of just one, or a small number, of kind(s) of produce. Monoculture farming allows the application of machinery to increase the efficiency of planting and harvesting and currently provides the lion's share of world food production [2]. However, monoculture farming has many disadvantages: increasing risk of disease and pest outbreaks, large amounts of pesticides, and soil exhaustion. The 1970 corn blight ruined more than 15% of corn crops in North America – because 70% of the crop being grown was the same high yield variety [13]. The European potato blight (Phytophthora infestans) of the mid 1840's caused extensive damage in Northern Europe, causing a million deaths in Ireland alone [33].

There is an alternate vision for agricultural robotics, where robots are used on small and family farms to allow alternatives to monoculture farming to compete with big agribusiness. The Digital Farmhand platform (Univ. of Sidney) is a low-cost, flexible-use platform specifically targeted at small farmers [29]. Livestock farming, especially in developing countries, is an essential small farm activity. The Univ. of Sidney Swagbot [11] is a novel platform designed for herding and ranching. It has a raised body with four independently driven wheels designed for locomotion on off-road terrain and unstructured environments. Furthermore, the robot is equipped with sensors to monitor the condition of the pastures and livestock it encounters. It is designed to launch a drone from its back as part of a collaborative herding process, [12], with the drone guiding the robot to locations of interest, though for now, a GPS-based tablet interface is used.

This approach comes with the challenge of operating under highly unstructured conditions, in particular changing temporal and spatial conditions: *"topography, soil structure and composition, vegetation landscape, visibility, illumination, and atmospheric conditions change at rates varying from seconds to months and on scales from millimeters to kilometers."* [4]. The livestock herding and grazing application is a good example, where robots would have to traverse difficult terrain in various seasons and weathers and often have to work with livestock where they are found rather than in designated or structured locations. There are many parts to meeting this challenge: the construction of the platform, algorithms for effective locomotion, design of sensors, interpretation of complex, natural imagery, communication backbone, flexible and robust wide-area navigation, interaction, and cooperation with other robots and with farmers. **In this work, we will focus on a specific but significant requirement for this kind of application: the flexible and robust wide-area navigation required to handle the navigation of robots to distant livestock and other task locations despite the changing visual appearance of the landscape due to weathers, seasons, and growth of vegetation and crops.**

Motivating Example: Consider the herding example of [12], with herding robot and associated drone. Some livestock have broken from the herd and need to be returned. The drone has found the distant animals but needs to let the robot know where they are so they can be returned to the herd. A typical approach to this problem would have the robot and drone construct a merged map as follows [27, 25, 1, 9, 28, 26, 22]:

- Both robot and drone must engage in exploratory actions, repeated at regular intervals, to construct their local maps [16]. The exploratory actions take the robots away from herding the livestock.
- The least complex map merging approach uses GPS to localize the robot and drone. However, researchers have shown that continual GPS is unreliable in an agricultural setting [3], which has proven a challenge for, e.g., automated tractor control in planting and harvesting and moving in orchards and forested areas.
- The robot can now path plan from its map. The path is only as good as the map information from prior exploratory actions. It may be outdated in this dynamic environment - perhaps a rainstorm resulted in debris blocking the path, ultimately causing traversal delays or failures.
- Once the robot arrives at the goal location, it will need to locate the missing animals, assuming they are still in the vicinity. Treating the goal as a map position was a shortcut: the goal is the animal's location.

Proposed Approach: We (Lyons and Rahouti) propose an alternate approach that addresses the changeability of the environment by focusing on mapless, visual coordination between team members - the robot and drone in this case [24, 18]. Map construction and use is a hugely important functionality for navigation, but we propose an additional robotic capability or functionality to handle this kind of agricultural navigation. We propose an alternate approach that addresses the changeability of the environment by focusing on map-less, visual coordination between team members - the robot and drone in this case [24, 18].

- Rather than using locations as navigation goals, we propose to use visual homing [32, 14, 34, 8] - an approach to move a robot to the vicinity where its imagery matches a goal image. This replaces the map position 'shortcut' with the actual objective of the task - move to the vicinity of the livestock.
- Rather than planning a navigation path in Cartesian 'map' space, we propose to plan the path in the space of shared, currently visible, visual landmarks between cooperating robots. This is a smaller space, restricted by the current line of sight visibility to currently unblocked and identifiable 'roadways' from each robot to the common landmark.
- Navigation is the process of identifying a sequence of common landmark images between pairs of robots (just two in our example) ending with the goal image. Visual homing is used to move to the vicinity of each landmark in turn and then to the final target.

To build the proposed approach, we address the following in this proposal:

1. Identification of candidate common landmarks within the visual field of each robot, with the criteria that the landmarks must be identifiable from another robot and should present a stable navigation target.
2. Communication of visual information between a widely distributed, heterogeneous robot team, with the criteria that the robots will not always be in contact and may contain errors.
3. Path selection in the space of common landmarks with the criteria of computational efficiency, timeliness, and robustness with respect to path segment failures due to environment uncertainty.
4. Navigation of a robot (or a group of robots) to a visual goal within its field of view where that goal has been constructed from an image taken by a different robot.

References

[1] Abraham Bachrach et al. Range - robust autonomous navigation in gps-denied environments. *IEEE/RSJ Int. Conf. on Int. Rob. & Sys. (IROS)*, 2010.

[2] A. Balough. The rise and fall of monoculture farming. *Horizon: The EU research and Innovation magazine*, Dec. 2021.

[3] Avital Bechar and Clement Vigneault. Agricultural robots for field operations: Concepts and components. *Biosystems Engineering*, 149, 2016.

[4] Avital Bechar and Clement Vigneault. Agricultural robots for field operations. part 2: Operations and systems. *Biosystems Engineering*, 153, 2017.

[5] J. S. Bergtold, R. L. Raper, and E. B. Schwab. The economic benefit of improving the proximity of tillage and planting operations in cotton production with automatic steering. *Applied Engineering in Agriculture*, 25(2), 2009.

[6] Simon Birrell, Josie Hughes, Julia Y. Cai, and Fumiya Iida. A field-tested robotic harvesting system for iceberg lettuce. *Journal of Field Robotics*, 37(2), 2020.

[7] Petra Bosilj, Erchan Aptoula, Tom Duckett, and Grzegorz Cielniak. Transfer learning between crop types for semantic segmentation of crops versus weeds in precision agriculture. *Journal of Field Robotics*, 37(2), 2020.

[8] Alireza Dirafzoon and Edgar Lobaton. Topological mapping of unknown environments using an unlocalized robotic swarm. In *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5545–5551. IEEE, 2013.

[9] S. Druen. Robotic navigation in gps-denied environments using the strapdown navigation algorithm with zero-velocity updates. *M.S. Thesis, Naval Postgraduate School*, 2020.

[10] T. Duckett, S. Pearson, S. Blackmore, and B. Grieve. Agricultural robotics: The future of robot agriculture. *UK-RAS White paper*, 2018.

[11] S. Eiffert, N. Wallace, H. Kong, and S. Pirmarzdashti, N.and Sukkarieh. Experimental evaluation of a hierarchical operating framework for ground robots in agriculture. *17th International Symposium on Experimental Robotics (ISER 2020)*, 2020.

[12] A. Hayward. Meet swagbot, the robot cowboy that can herd and monitor cattle on its own. *Smithsonian magazine*, July 2016.

[13] Tatum LA. The southern corn leaf blight epidemic. *Science*, March 1971.

[14] H.-C. Lee, S.-H. Lee, D.-J. Kim T.-S. Lee, and B.-H. Lee. A survey of map merging techniques for cooperative-slam. 2012.

[15] Chris Lehnert, Chris McCool, Peter Corke, Inkyu Sa, Cyrill Stachniss, Eldert J. van Henten, and Juan Nieto. Special issue on agricultural robotics part 1 and 2. *Journal of Field Robotics*, 37(1) and 37(2), 2020.

[16] Iker Lluvia, Elena Lazkano, and Ander Ansuategi. Active mapping and robot exploration: A survey. *Sensors*, 21(7), 2021.

[17] António P. Moreira Luiz F. P. Oliveira and Manuel F. Silva. Advances in agriculture robotics: A state-of-the-art review and challenges ahead. *MDPI Robotics*, 52(10), 2021.

[18] Damian Lyons and Noah Petzinger. Visual homing for robot teams: Do you see what i see? *SPIE Conference on Unmanned Systems Technology (UST)*, April 2022.

[19] Chris Lytridis, Vassilis Kaburlasos, Theodore Pachidis, Michalis Manios, Eleni Vrochidou Theofanis Kalampokas, and Stamatis Chatzistamatis. An overview of cooperative robotics in agriculture. *Agronomy*, 11, 2021.

[20] E. Morimoto, M. Suguri, and M. Umeda. Vision-based navigation system for autonomous transportation vehicle. *Precision Agriculture*, 6(3), 2005.

[21] United Nations. Global population growth and sustainable development. *DESA/POP/2021/TR/No.2 2021*, 2021.

[22] P. C. Niedfeldt, A. Speranzon, and A. Surana. Distributed map fusion with sporadic updates for large domains. *IEEE International Conference on Robotics and Automation*, 2015.

[23] R. Oberti and S. Shapiro. Special issue: Robotic agriculture. editorial: Advances in robotic agriculture for crops. *Biosystems Engineering*, 146, 2016.

[24] Mohamed Rahouti and Damian M. Lyons. Wavn: Wide area visual navigation for large-scale, gps-denied environments. *IEEE Int. Conf. on Robotics & Aut.*, May 2023.

[25] R. Reid and T. Braunl. Large-scale multi-robot mapping in magic 2010. *IEEE 5th International Conference on Robotics, Automation and Mechatronics (RAM)*, 2011.

[26] S. Saeedi, M. Trentini, M. Seto, and H. Li. Multiple-robot simultaneous localization and mapping: A review. *Journal Field Robotics*, 33(1), 2016.

[27] Davide Scaramuzza et al. Vision controlled micro flying robots. *IEEE/ Rob. & Aut. Magazine*, Sept. 2014.

[28] JR Sánchez-Ibáñez, CJ Pérez-Del-Pulgar, and A García-Cerezo. Path planning for autonomous mobile robots: A review. *Sensors (Basel)*, 21(23), 2021 Nov 26.

[29] S Sukkarieh. Mobile on-farm digital technology for smallholder farmers. *2017 Crawford Fund Annual Conference on Transforming Lives and Livelihoods: The Digital Revolution in Agriculture*, 2017.

[30] Y. Xiong, Y. Ge, L. Grimstad, and P. From. An autonomous strawberry-harvesting robot: Design, development, integration, and field evaluation. *Journal of Field Robotics*, 37(2), 2020.

[31] C. Yang, J. Everitt, Q. Du, B. Luo, and J. Chanussot. Using high-resolution airborne and satellite imagery to assess crop growth and yield variability for precision agriculture. *Invited paper, proceedings IEEE*, 10(3), Mar. 2013.

[32] Shuien Yu, Chunyun Fu, Amirali K Gostar, and Minghui Hu. A review on map-merging methods for typical map types in multiple-ground-robot slam solutions. *Sensors*, 20(23):6988, 2020.

[33] J. C. Zadoks. The potato murrain on the european continent and the revolutions of 1848. *Potato Research*, 51, 2008.

[34] Xun S. Zhou and Stergios I. Roumeliotis. Multi-robot slam with unknown initial correspondence:the robot rendezvous case. 2006.