The International Society of Precision Agriculture presents the
15th International Conference on Precision Agriculture
26–29 JUNE 2022
Minneapolis Marriott City Center | Minneapolis, Minnesota USA

Agricultural Robots Classification based on Clustering by Features and Function

Maurizio Canavari, Marco Medici, Giacomo Rossetti

Department of Agricultural and Food Sciences, Alma Mater Studiorum – University of Bologna, Viale Fanin 50, 40127 Bologna - Italy

Abstract

Robotic systems in agriculture (agrobots) have become popular in the last few years. They represent an opportunity to make food production more efficient, especially when coupled with technologies such as the Internet of Things and Big Data. Agrobots bring many advantages to farm operations: they can reduce human fatigue and work-related accidents. In contrast, their large-scale diffusion is today limited by a lack of clarity and exhaustiveness in the regulatory framework that is intrinsically tied with ethical and legal issues concerning the management of agrobots and information. Existing legislation places obligations, like machine registration and human supervision in operations, with several issues to be addressed. They concern, to name but a few, the legal responsibility, machine and human data management, privacy issues, and contractual limitations.

In this context, obtaining a clear taxonomy of agrobots would facilitate addressing management and legal issues, opening up the possibility of setting specific policies and market strategies based on recurring characteristics and features. This study aims to pursue an exhaustive classification of the various types of agrobots available today. An observational survey method involved a web search of agrobots followed by contact by phone with agrobot producer company representatives resulted in a set of qualitative variables accounting for criteria describing the scope of agrobot operation. The study reports homogeneous groups (clusters) of agrobots characterized by minimum classification redundancy.

This classification provides useful information for the refinement of ad-hoc legislative supports accounting for the various types of agrobots, the promotion of market segmentation practices by technological providers, and the creation of ad-hoc fleet management strategies in the farm context.

Keywords
agrobots, unmanned vehicles, robotics, agricultural machinery, clustering.

1. Introduction

The use of robotic solutions in agriculture heavily increased in recent years and represents an opportunity to improve crop production [1–3]. To date, robotics has been implemented with success in open field and indoor applications; among the various functions, agricultural robots can carry out weeding, fertilization, harvest, and other agricultural operations more effectively and efficiently, allowing economic and environmental benefits to be achieved[4]. The growing trend also involved automatic technologies for dairy and livestock, with the adoption of automatic milking systems, robots for feeding, and technologies for manure management becoming key success factors in many farms [5–7]. Agricultural robots performing water irrigation, spraying, pruning, harvesting, monitoring, and accounting for land preparation can automate a large piece of agricultural production, especially those slow and repetitive tasks for farmers, reducing human workload and optimizing times and costs[3,8]. Being able to carry out hard physical tasks hitherto covered by farmers and potentially ensuring night work cycles, these systems accompany many advantages, such as reducing work-related accidents and the autonomous conduction of potentially dangerous operations for human health like pesticide application[9,10].

To date, a formal definition for the term "agricultural robot" or "agrobot" is missing, and at the same time, the features of robots performing agricultural operations are scarcely recognized by jurisdictions. Recently, Lowenberg-DeBoer et al. proposed to define the field crop robot as "a mobile, autonomous, decision making, mechatronic device that accomplishes crop production tasks [...] under human supervision, but without direct human labor"[11]. Other authors have proposed to define agricultural robots as programmable machines performing various agricultural tasks, such as cultivation, transplanting, spraying, and selective harvesting[12]. These definitions indicate that agricultural robots are a set of heterogeneous systems composed of various technologies designed for a large variety of uses in the broad domains of the agri-food sector.

Notwithstanding their various features and benefits, the large-scale diffusion of agricultural robots is also limited today by a number of barriers. Current challenges for the commercial viability of robots span from technical factors concerning the degree of autonomous operation to financial reasons since technology providers hardly raise revenues during the initial years of the activity[13]. In addition, often, farmers who are the potential adopters lack sufficient skills and expertise concerning ICT and data analysis.

Also, the development of the autonomous equipment sector heavily depends on the legal and regulatory framework. Currently, many European jurisdictions lack exhaustiveness concerning the use and management of several types of robots[14]. Uncertainty is related to the possibility that robots will eventually prove to be better than humans at important tasks and, as a consequence, governments may come to be subject to ethical and political pressure to forbid agricultural tasks to humans[15]. Another point is the extent and nature of the contracts between technology providers and final users concerning data management. In theory, the collection, storage, and use of the agricultural data collected can only take place after the originator of the data has granted his consent through a contractual agreement, and the data originator can be either the farmer, the provider, or the contractor, depending on the contract terms and the nature of technology (e.g., firmware, open source). In addition to this, obligations by farmers when they use robots may be susceptible to modification by regulation[16], while issues concerning civil responsibility and privacy still have to be comprehensively addressed. Given these considerations, it is expected that governments will become more accommodative in the future, supporting innovative companies and farmers with tax reduction or subsidy schemes to boost the adoption of the technology.

To date, a clear and agreed classification of the various types of agricultural robots is missing. Aimed at bridging this gap, the main objective of this study is to obtain a robot classification based on observable features to better define the regulatory aspects and facilitate the production of ad-hoc legislative instruments, and provide a comprehensive framework for technology users and developers to allow market segmentation practices.

2. Materials and Methods

The survey method has involved a web search of robots and systems, which were described with qualitative variables based on specific criteria describing their usage in farms. The web search was performed by using the search tags "agricultural robots", "agrobot", "agricultural robot companies", as well as queries including the various agricultural activities, such as "weeding robot" and "harvest robot". Four inclusion criteria were considered to guarantee an acceptable level of information quality (Table 1).

Table 1. Inclusion criteria of sources

Inclusion criteria	Rationale
The source reported exhaustive textual or numerical descriptions.	Quantitative or qualitative information is necessary to make comparisons between technologies.
The described technology was able to perform operations autonomously.	Systems performing tasks not autonomously are out of the scope of this study.
The source provided information was not conditioned by site subscription.	Most companies avoided to spread information for non-commercial purposes.
The source reported information concerning working technology at least at TRL 7.	System prototypes not demonstrated in an operational environment are considered less relevant to producing insights on current state-of-the-art technology.

Following this procedure, several technologies were assessed for eligibility. A total of 246 items were finally identified and included in the analysis. Data were input in an Excel file using 35 descriptive variables (in addition to the manufacturing company, company location, brand(s), website, and robot name information):

- production domain: agriculture "AGR", livestock "LIV";
- activity environment: outdoor "OUT", indoor, "IN";
- place of activity: open field "FIELD", industrial setting "IND", stable "STA";
- type of machine: single-purpose robot "SINGLE", drone "DRO", multi-task robot "MULT";
- type of moving: fixed "FIXED", self-propelled "SELFP", pulled "PULLED", on-track "TRACK";
- activity carried out: crop monitoring "CROP_M", logistic operations "LOGI", irrigation "WATER", chemical weeding "WEED_C", mechanical weeding "WEED_M", crop defence "DEF", fertilisation "FERT", harvesting "HARV", pruning "PRUN", sowing "SOW", harrowing "HARROW", animal washing "ANIM_WASH", animal feed "ANIM_FEED", milking "MILK", grafting "GRAFT", soil mixing "SOIL_MIX", tray filling or washing "TRAY";
- energy supply: diesel/petrol fuel "FUEL", hybrid or battery "HYB", power cable "POWC", attached to tractor "TRACT".

The procedure included the following steps: factor analysis, hierarchical, and k-means clustering.

2.1 Factor analysis

Given the relatively high ratio between the number of observations and the number of variables (~7:1), factor analysis was applied in order to express data variability with the least but significant number of factors. Tetrachoric correlation was used to measure the correlation between the 35 binary variables: a latent bivariate normal distribution for each pair of binary variables was assumed, and the tetrachoric correlation coefficient *rho* was estimated. The correlation matrix thus obtained was taken as an input to perform the factor analysis, with the aim to reduce the number of variables into fewer factors accounting for a sufficient level of variance. Keeping enough factors to account for at least 70% of the variance was the criterion used to determine the number of factors. The *varimax* factor structure was used as rotation algorithm. Tetrachoric correlation was calculated using the package *psych* available for R[18].

2.2 Hierarchical clustering

Hierarchical clustering was used to assess the number of clusters. The resulting dendrogram helped visualize the distances between the different numbers of clusters and the cluster(s) characterized by the minimum number of items. Hierarchical clustering was performed in R using the function *hclust*.

2.3 *K-means* clustering

K-means clustering[19] was performed based on extracted factors and the resulting factor scores. The cluster centers (i.e., *medioids*) of the clusters identified with the *hclust* function were used as starting points of *k-means* clustering. One-way ANOVA and Tukey's HSD tests were run to explore possible differences among clusters and perform multiple pairwise-comparisons.

3. Results

The distribution of the 35 binary variables describing the 246 agrobots identified and included in the analysis is shown in Table 2. The dataset is freely available at: http://docs.google.com/spreadsheets/d/1ZnWBZdAiEoJNxt6VTslmiwHGfAO0U4kRkRgxxZXd6a4/edit#gid=0.

Table 2. Distribution of binary variables across the collected items

Domain	Variable	Label	Distribution
Production context	Agriculture	AGR	79.7%
	Livestock	LIV	20.3%
Working environment	Indoor	IN	61.8%
	Outdoor	OUT	42.3%
Place of activity	Open field	FIELD	40.2%
	Industry	IND	40.2%
	Stable	STA	20.3%
Type of machine	Single-purpose	SINGLE	84.1%
	Drone	DRO	10.2%
	Multi-purpose	MULT	6.5%
Type of moving	Fixed	FIXED	34.1%
	Self-propelled	SELFP	53.3%
	Pulled	PULLED	3.7%
	On-Track	TRACK	8.9%
Type of activity	Crop monitoring	CROP_M	18.3%
	Logistic operations	LOGI	11.4%
	Irrigation	WATER	4.9%
	Chemical weeding	WEED_C	17.5%
	Mechanical weeding	WEED_M	13.4%
	Crop defence	DEF	4.5%
	Fertilisation	FERT	2.8%
	Harvesting	HARV	10.6%
	Pruning	PRUN	0.4%
	Sowing	SOW	12.2%
	Harrowing	HARR	2.4%
	Animal washing	ANIM_WASH	5.3%
	Animal feed	ANIM_FEED	10.2%
	Milking	MILK	4.9%
	Grafting	GRAFT	2.8%
	Soil mixing	SOIL_MIX	2.8%
	Tray filling/washing	TRAY	8.1%
Type of energy supply	Diesel/petrol	FUEL	8.1%
	Hybrid/battery	HYB	43.5%
	Power cable	POWC	44.7%
	Attached to tractor	TRACT	3.7%

Seven factors, accounting for the most significant robot features, were identified (Figure 2). The relative cumulative variance associated with the factors yielded 0.718. The factors can be described as follows:

- Factor 1, accounting for the production domain of agriculture;
- Factor 2, describing fixed single-purpose machines;
- Factor 3, describing self-propelled stand-alone technologies operating in open field;
- Factor 4, describing fixed multi-tasking machines;
- Factor 5, accounting for agricultural robots used indoor at industrial level;
- Factor 6, describing technologies using agricultural inputs (e.g., fertilizers, pesticides, seeds, water);

- Factor 7, describing technologies mainly used for livestock.

The number of clusters (k=5) was iteratively selected as optimal, starting from a 10 clusters dendrogram applied to the binary dataset and decreasing this number until the number of items in the smaller cluster was higher than seven.

Clusters are described as follows:

- Cluster #1 (n=14). Robots using agronomic inputs. This small set includes technologies using agricultural inputs when performing agricultural operations like fertilization, sowing, weeding, and pest control.
- Cluster #2 (n=64). Indoor livestock robotics. This cluster consists of robots for livestock rearing, and operating indoor. They include technologies used for feeding animals and washing and sanitizing stables and kennels.
- Cluster #3 (n=17). Single-purpose UGVs and implements. This small cluster includes automated technologies used with or propelled by other agricultural machines like tractors.
- Cluster #4 (n=58). Fixed single-purpose machines. This set contains technologies used in indoor and in an industrial environment, with electrical energy supplied by a power cable.
- Cluster #5 (n=93). Monitoring technology. This large set includes both unmanned aerial vehicles (UAVs) mounting technology for soil and canopy sensing and indoor monitoring technology, like, for instance, in greenhouses.

In the one-way ANOVA tests, the observed p-value was significant for every cluster (<0.01).Tukey multiple pairwise-comparisons highlighted the presence of at least three statistically significant differences between each pairs of cluster (Table 3).

Table 3. Tukey multiple comparisons of means

Clusters	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
2-1	0.001	0.631	0.002	0.000	0.000	0.000	0.000
3-1	0.645	0.832	0.000	0.000	0.652	0.000	0.000
4-1	0.997	0.000	0.007	0.000	0.091	0.000	0.356
5-1	0.915	0.024	0.055	0.000	0.525	0.000	0.756
3-2	0.000	0.999	0.000	0.999	0.000	0.044	0.001
4-2	0.000	0.000	0.989	0.771	0.000	0.122	0.000
5-2	0.000	0.048	0.267	0.026	0.000	0.705	0.000
4-3	0.198	0.000	0.000	0.981	0.886	0.754	0.000
5-3	0.874	0.359	0.000	0.242	0.999	0.003	0.000
5-4	0.243	0.000	0.616	0.000	0.376	0.002	0.740

The most significant differences across clusters were clearly observed for factors 2, 3, 4, 6, and 7, for which a single cluster emerged among the others (Figure 1). Regarding factor 1, all clusters were considered except for cluster #2, while for factor 5 clusters #4 and #5.

4. Discussion

Overall, the cluster analysis performed gave reasonable results, providing interesting insights.

A general set of multi-purpose robots used for agricultural operations, identified by Cluster #1, includes robots operating in the open field and protected environment, able to carry out various agricultural operations; the peculiarity of this group is the fact that most of the included technologies use agronomic inputs (e.g., fertilizers, pesticides, herbicides, irrigation water, seeds) in a quite effective and efficient way, thereby leaving a reduced footprint to the environment in comparison with traditional technologies. If, on the one hand, these novel technologies can mitigate much of the negative externalities that often characterize conventional agriculture[4], on the other hand, they should be subjected to specific operating rules allowing good production levels without harming the environment. Apparently, Cluster #1 is the less populated cluster, and this may be due to the fact that autonomous robots like UGVs have several limitations today, like the impossibility to survey large agriculture fields rapidly[20] as well as their high investment cost.

Cluster #2 includes systems used in the large domain of livestock and animal rearing, such as robots that autonomously manage feedings and also systems for the sanitation of environments. These technologies constitute relevant support for farmers in terms of time savings and health safeguards and must comply with health safety regulations.

Cluster #3 is a heterogeneous group including ground open-field technology like UGVs and technologically advanced implements to be attached to tractors at least for the energy supply. These single-purpose technologies account for a large number of operations (e.g., harvesting, crop monitoring, mechanical weeding, and logistic operations). This large heterogeneity poses practical difficulties in addressing this set with a unique shared regulation. Rather, it would deserve further analysis to better differentiate the various systems, while needing additional observations.

Cluster #4 represents a family of industrial fixed robots needing direct electrical supply; they are mostly fixed indoor systems, used, for example, in technological nurseries or to automate sowing or transplanting in an indoor environment. These technologies can be used both in agriculture and in livestock domain, but limited to milking.

Cluster #5 includes technologies performing crop monitoring and canopy sensing, including UAVs, in the agricultural domain. Unlike other technologies, these systems require ICT knowledge and skills to harness sensor technology as well as operate agriculture drones. Probably these systems are the ones more subjected to technological obsolescence. Note that although UAVs can be used for pesticide application and fertilization, their use in these domains are restricted in several countries because aerial application of pesticides is not allowed. In light of this, the creation of two distinct cluster #1 and #5 accounting, respectively, for spraying application and not, even with a similar technology, sounds fine.

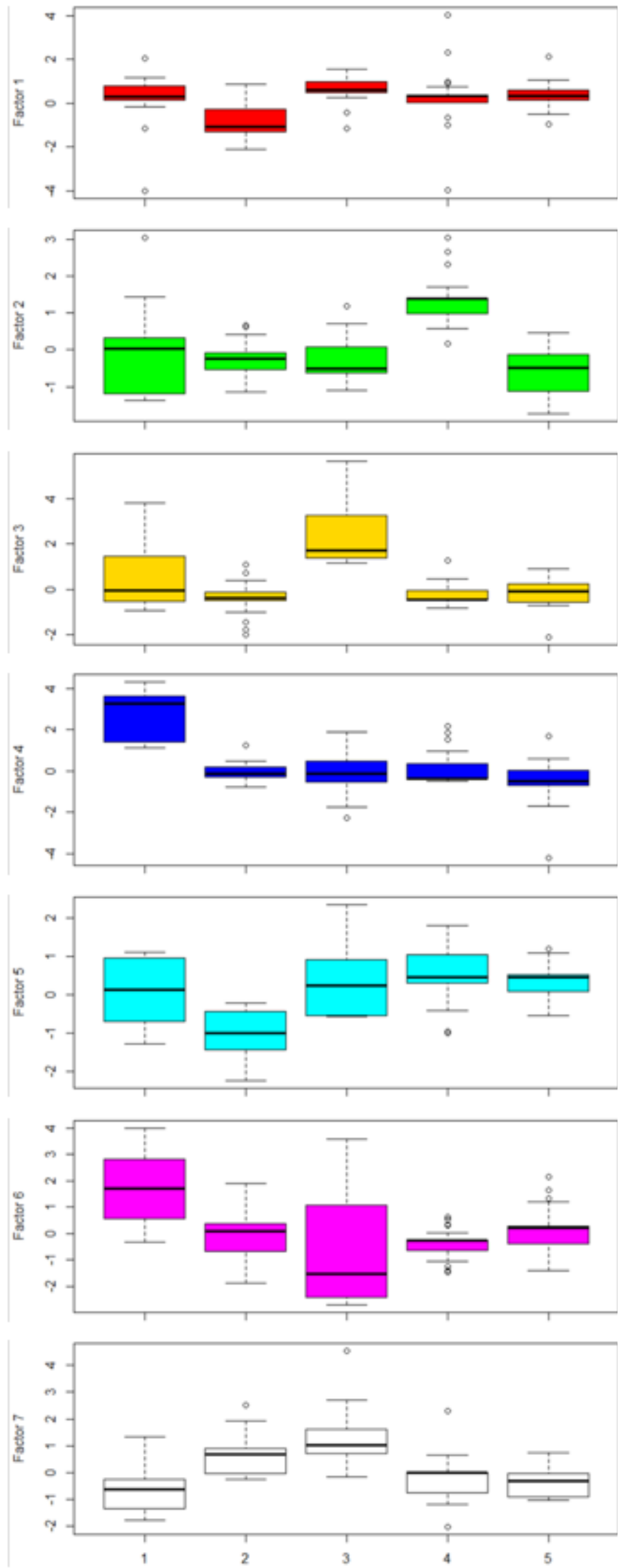

Fig 1. Tested factors among clusters

5. Conclusions

This study provided useful insights for the creation of homogeneous groups of robots, in a sample consisting of 246 devices. The study can open up the possibility of setting specific regulatory policies and market strategies based on recurring characteristics within clusters.

This research has some limitations. Incomplete information is obtainable by screening websites since many companies are reluctant to share information if not for business purposes. One step ahead in robot classification could be the achievement of a common and shared set of properties and functions describing, e.g., the types of production and activity, and the working environment.

The classification covering various domains proposed in this study can guide more precise technology classifications based on phenotypisation in the field of ontology design. In this context, robot attributes can be defined by properties and entities describing other features, such as the production context, the working environment, the place of activity, the modularity and the interoperability level, the type of moving, energy supply, and activity carried out.

References

(1) Benke, K.; Tomkins, B. Future Food-Production Systems: Vertical Farming and Controlled-Environment Agriculture. *Sustain. Sci. Pract. Policy* **2017**, *13* (1), 13–26. https://doi.org/10.1080/15487733.2017.1394054.

(2) Rose, D. C.; Wheeler, R.; Winter, M.; Lobley, M.; Chivers, C. A. Agriculture 4.0: Making It Work for People, Production, and the Planet. *Land use policy* **2021**, *100*, 104933. https://doi.org/10.1016/j.landusepol.2020.104933.

(3) Vasconez, J. P.; Kantor, G. A.; Auat Cheein, F. A. Human–Robot Interaction in Agriculture: A Survey and Current Challenges. *Biosyst. Eng.* **2019**, *179*, 35–48. https://doi.org/10.1016/J.BIOSYSTEMSENG.2018.12.005.

(4) Medici, M.; Pedersen, S. M.; Carli, G.; Tagliaventi, M. R. Environmental Benefits of Precision Agriculture Adoption. *Econ. Agro-Alimentare* **2019**, *21* (3). https://doi.org/10.3280/ECAG2019-003004.

(5) Pezzuolo, A.; Cillis, D.; Marinello, F.; Sartori, L. Estimating Efficiency in Automatic Milking Systems. *Eng. Rural Dev.* **2017**, *16*, 736–741. https://doi.org/10.22616/ERDEV2017.16.N148.

(6) Salfer, J. A.; Minegishi, K.; Lazarus, W.; Berning, E.; Endres, M. I. Finances and Returns for Robotic Dairies. *J. Dairy Sci.* **2017**, *100* (9), 7739–7749. https://doi.org/10.3168/JDS.2016-11976.

(7) Sharipov, D. R.; Yakimov, O. A.; Gainullina, M. K.; Kashaeva, A. R.; Kamaldinov, I. N. Development of Automatic Milking Systems and Their Classification. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *659* (1), 012080. https://doi.org/10.1088/1755-1315/659/1/012080.

(8) Yaghoubi, S.; Akbarzadeh, N. A.; Bazargani, S. S.; Bazargani, S. S.; Bamizan, M.; Asl, M. I. Autonomous Robots for Agricultural Tasks and Farm Assignment and Future Trends in Agro Robots. *Int. J. Mech. Mechatronics Eng.* **2013**, *13* (3), 1–6.

(9) Oliveira, L. F. P.; Moreira, A. P.; Silva, M. F. Advances in Agriculture Robotics: A State-of-the-Art Review and Challenges Ahead. *Robot. 2021, Vol. 10, Page 52* **2021**, *10* (2), 52. https://doi.org/10.3390/ROBOTICS10020052.

(10) Meshram, A. T.; Vanalkar, A. V.; Kalambe, K. B.; Badar, A. M. Pesticide Spraying Robot for Precision Agriculture: A Categorical Literature Review and Future Trends. *J. F. Robot.* **2022**, *39* (2), 153–171. https://doi.org/10.1002/ROB.22043.

(11) Lowenberg-DeBoer, J.; Behrendt, K.; Canavari, M.; Ehlers, M.-H.; Gabriel, A.; Huang, I.; Kopfinger, S.; Lenain, R.; Meyer-Aurich, A.; Milics, G.; Olagunju, K. O.; Pedersen, S. M.; Rose, D.; Spykman, O.; Tisseyre, B.; Zdráhal, I. 85. The Impact of Regulation on Autonomous Crop Equipment in Europe. *Precis. Agric. '21* **2021**, 711–717. https://doi.org/10.3920/978-90-8686-916-9_85.

(12) Bechar, A.; Vigneault, C. Agricultural Robots for Field Operations: Concepts and Components. *Biosyst. Eng.* **2016**, *149*, 94–111.

https://doi.org/10.1016/J.BIOSYSTEMSENG.2016.06.014.

(13) Gil, G.; Casagrande, D.; Cortés, L. P.; Verschae, R. Why the Low Adoption of Robotics in the Farms? Challenges for the Establishment of Commercial Agricultural Robots. *Smart Agric. Technol.* **2023**, *3*, 100069. https://doi.org/10.1016/J.ATECH.2022.100069.

(14) Basu, S.; Omotubora, A.; Beeson, M.; Fox, C. Legal Framework for Small Autonomous Agricultural Robots. *AI Soc.* **2020**, *35* (1), 113–134. https://doi.org/10.1007/s00146-018-0846-4.

(15) Sparrow, R.; Howard, M. When Human Beings Are like Drunk Robots: Driverless Vehicles, Ethics, and the Future of Transport. *Transp. Res. Part C Emerg. Technol.* **2017**, *80*, 206–215. https://doi.org/10.1016/J.TRC.2017.04.014.

(16) Sparrow, R.; Howard, M. Robots in Agriculture: Prospects, Impacts, Ethics, and Policy. *Precis. Agric. 2020 223* **2020**, *22* (3), 818–833. https://doi.org/10.1007/S11119-020-09757-9.

(17) Fabiano, N. Robotics, Big Data, Ethics and Data Protection: A Matter of Approach. In *Intelligent Systems, Control and Automation: Science and Engineering*; Springer Netherlands, 2019; Vol. 95, pp 79–87. https://doi.org/10.1007/978-3-030-12524-0_8.

(18) RCoreTeam. R: A Language and Environment for Statistical Computing. Vienna, Austria 2020.

(19) Kanungo, T.; Mount, D. M.; Netanyahu, N. S.; Piatko, C.; Silverman, R.; Wu, A. Y. Analysis of a Simple K-Means Clustering Algorithm. *Proc. Annu. Symp. Comput. Geom.* **2000**, 100–109. https://doi.org/10.1145/336154.336189.

(20) Liu, X.; Chen, S. W.; Nardari, G. V.; Qu, C.; Ojeda, F. C.; Taylor, C. J.; Kumar, V. Challenges and Opportunities for Autonomous Micro-UAVs in Precision Agriculture. *IEEE Micro* **2022**, *42* (1), 61–68. https://doi.org/10.1109/MM.2021.3134744.