The SAGA concept: Swarm Robotics for Agricultural Applications

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Abstract Robotics is expected to play a major role in the agricultural domain, and often multi-robot systems and collaborative approaches are mentioned as potential solutions to improve efficiency and system robustness. Among the multi-robot approaches, swarm robotics stresses aspects like flexibility, scalability and robustness in solving complex tasks, and is considered very relevant for precision farming and large-scale agricultural applications. However, swarm robotics research is still confined into the lab, and no application in the field is currently available. In this paper, we describe a roadmap to bring swarm robotics to the field within the domain of weed control problems. This roadmap is being instantiated within the SAGA experiment, founded within the context of the ECHORD++ European project. Together with the experiment concept, we introduce baseline results for the target scenario of monitoring and mapping weed in a field by means of a swarm of UAVs.

1 Introduction

Despite being studied for about 20 years, swarm robotics is still confined into laboratory settings [8, 23, 9] and no commercial application can be acknowledged to date, to the best of our knowledge. This has several reasons, including the need for cost-effective hardware solutions, the lack of established user-swarm interaction methodologies, and the need of convincing use-cases and business models. Nevertheless, research in swarm robotics has produced

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a large knowledge base that can be exploited to deliver concrete applications [6, 27]. Additionally, several proposals have been advanced to provide engineering methods for swarm robotics, independently of the specific domain [11, 3, 21]. Hence, time is mature for the last missing step: approaching a concrete real-world problem with a genuine swarm robotics approach.

Concerning real-world problems, agriculture represents a very challenging and increasingly important domain to be tackled by robotics solutions. Beyond mere automation, robots offer additional means to truly implement a precision agriculture approach [1, 10]. In this respect, distributed autonomous robotic systems stand as appealing solutions. Indeed, agricultural problems are characterised by unstructured environments, large spatial distributions and heterogeneities that naturally call for flexible and robust multi-robot approaches. The application of swarm intelligence to agricultural robotics can lead to disruptive innovation, thanks to the miniaturisation of hardware and the cooperation within a highly redundant system. On the one hand, miniaturisation would allow to apply solutions only when and where they are really needed, avoiding soil compaction typical of large machines and bringing the concept of precision agriculture to the highest realisation thanks to proximal sensing and actuation [14]. On the other hand, redundancy and cooperation within a distributed robotic system can provide resilience and robustness to faults, and can result in super-linear performance, so as to maximise the effectiveness of the group as a whole beyond the sensing and information-processing abilities of individual units (e.g., exploiting biological models of information retrieval and integration [2, 21]).

Among the different problems faced in precision agriculture, automated weed control is certainly a priority to reduce labor and operation costs, while maximising yield and minimising/avoiding the usage of chemicals. Autonomous weed control systems require (i) efficient navigation within the field, (ii) automatic detection and identification of weeds, (iii) mechanisms for individual weed removal and control, and (iv) field mapping to support decision-making at a global scale [25]. Out of the above issues, weed recognition and field mapping still represent important challenges for an automatic weed control system [24, 25]. In this respect, various robotic solutions are being developed, with unmanned aerial vehicles (UAVs) recently having a large share, thanks to (i) the reduced costs and the increased reactivity and resolution with respect to satellite or other aerial photogrammetry technologies, and (ii) the ability to move over and rapidly map the field at a higher speed with respect to ground vehicles [4, 28]. Despite recent efforts, commercial applications are still underdeveloped, and progress is still required in both automatic recognition and mapping [24].

Monitoring and mapping is a task that can be suitably tackled with a swarm robotics approach. By exploiting the power of collective intelligence, it is possible to overcome the individual perceptual limitations and deal with uncertain environmental conditions (e.g., due to plant differences and changing weather conditions). As weed tends to grow in patches over the field, a precise mapping can be achieved by allocating more resources/time to such patches, while other areas can be only mildly monitored. A uniform coverage is therefore sub-optimal, while a flexible and adaptive strategy can be more efficient, especially if carried out in a parallel/coordinated way by a robot swarm. Starting from these insights, we have developed a roadmap for the application of a genuine swarm robotics approach to the weed monitoring/mapping problem, which is discussed in Section 2. This roadmap is implemented within the experiment SAGA: Swarm robotics for AGricultural Applications. The experiment is founded within the context of the ECHORD++ EU Project,[1] and aims to demonstrate the usage of a group of small UAVs to collectively monitor a field and distributedly map the presence of weeds. Such an autonomous monitoring/mapping system can drastically reduce the costs of timely detection and supports an optimal planning (both for operation timing and field coverage) of weed removal.

The paper is organised as follows. In Sect. 2, we discuss the concept and the starting point of the roadmap in relation to the state of the art, and we indicate the activities planned to tackle the weed monitoring and mapping problem described above. In Sect. 3, we introduce an abstract model for multi-robot field monitoring, and we describe baseline results obtained with a simple decentralised approach. Sect. 4 closes the paper with some discussions and perspective on the commercial application of swarm robotics solutions for the agricultural domain.

2 Concept and background

Weed monitoring and mapping is a tough problem that determines the daily activities in a farm. Fig. 1 (left) shows a typical situation after planting seedlings, with small weeds emerging due to field irrigation. In current organic farming practice, weeds of this size are mechanically removed using machines that do not harm the young crop. These machines only work if the weeds have a specific small size: act too early and weed would re-emerge, intervene too late and weed would not be removed efficiently. Therefore, the timing of this operation is crucial. To decide which areas to weed when, farmers spend a lot of time monitoring their fields. The system proposed within the SAGA experiment aims to take over this monitoring task, and to generate task maps for future autonomous weeding robots, telling them which areas to work on and how to plan their paths.

More specifically, SAGA will provide an automatic weed monitoring and mapping system by means of a swarm of UAVs able to patrol the field, recognise the presence of weeds, dedicate resources to the most interesting areas and collectively build a field map indicating areas with different urgency

[1] Founded under the EU's 7th Framework Programme (ID: 601116), see `http://echord.eu`

Fig. 1 Left: Young lettuce crop (1) with two types of surfacing weeds (2 and 3). In SAGA, we will perform object detection or semantic segmentation on images like this. Right: a close-up view of the PrecisionScout, the UAV produced by Avular B.V. and exploited within the SAGA experiment.

of intervention. All this is to be obtained through a genuine swarm robotics approach, featuring decentralised control and flexible and scalable behaviour.

In this way, SAGA instantiates a roadmap for the demonstration of swarm robotics applied to precision farming. The SAGA concept represents a novelty within the agricultural robotics domain, despite significant effort and resources being dedicated to agricultural robotics research, including multi-robot approaches. For instance, *RHEA* and *Flourish* focus on the coordination mechanisms for multiple ground and/or aerial vehicles; *ASETA* [12] focuses on mapping weeds with a UAV; and the ECHORD++ experiment *MARS* deploys a group of ground robots for seeding operations.[2] In all these projects, collaboration between one or more UAVs and/or one or more unmanned ground robots is envisaged, exploiting planning for multi-robot coordination. However, results are still very preliminary, and none of the above projects takes a genuine swarm robotics approach. In contrast, we propose a solution to the monitoring and mapping problem that is completely decentralised, so that desired properties like robustness and scalability are taken into account at design time.

2.1 Collective-level monitoring and mapping

The collective-level control is responsible for the overall mission accomplishment. Instead of a-priori planning the mission for the whole group, we will exploit swarm robotics techniques in which the group behaviour emerges from self-organisation, hence providing flexibility, robustness to faults and scalability with group size. Our goal is to devise collective strategies with an optimal trade-off between distributed exploration and timely weed recognition.

[2] *RHEA*: `http://www.rhea-project.eu`; *Flourish*: `http://flourish-project.eu`; *MARS*: `http://echord.eu/mars`. Websites accessed on July the 5th, 2016.

The study of the collective monitoring and mapping behaviour will be initially performed in simulation (see also Section 3), and different bio-inspired algorithms will be evaluated. In particular, we will consider honeybee foraging and collective decision-making as source of inspiration, and will exploit a design pattern to implement such behaviours in UAV swarms [20, 21]. This will provide the mechanisms to explore the field and allocate resources during the monitoring activities: UAVs will be recruited to monitor those areas in the field that have been identified as potentially containing weed patches, while weedless areas are quickly abandoned by the swarm. In this way, resource allocation is adapted to the field heterogeneities, and error-prone individual inspection will be compensated for through collaborative re-sampling. Additionally, we will consider the emergence of a categorisation system from peer-to-peer interactions [2], and implement a collective mapping behaviour as a categorisation problem of different areas of the field, so that labelling of different areas will result from a consensus process among the UAVs that individually estimated the presence of weeds.

2.2 On-board vision for weed detection and navigation

The on-board vision system of each individual UAV has to perform object detection or semantic segmentation on images like in Fig. 1 (left), to count the number of weeds above a specific size or otherwise measure their development. The results of each image have to be mapped to real-world coordinates, using absolute and relative pose estimates from other sensors (e.g., GPS, IMU). This provides the basis for timing and path planning as described above.

Current robotics approaches employ unmanned vehicles (e.g., Bonirob [4]) for weed detection and removal [19, 18, 15]. As demarcation strategy, Bonirob and similar platforms use a protective cover with artificial lighting and cameras underneath. This is a suboptimal solution that simplifies the vision problem with constant, shadowless light conditions.

In previous work, we demonstrated the use of SURF features, bag-of-visual-words clustering, and support vector machines (SVMs) to classify image patches as crop or weed [26]. This method can handle strong light variations and shadows from direct sunlight. The approach can be combined with a sliding window approach or selective search to detect objects in the whole image. Another option is to oversegment images into superpixels, and then perform feature extraction and classification on each superpixel (i.e., semantic segmentation), optionally improved with smoothness-based and other priors (e.g., exploiting the expected crop pattern). For both approaches, prior background removal can be beneficial. These methods need to be adapted for usage on the UAVs, exploiting the on-board camera and processing power.

On-board vision can also support the individual motion control. In [5], modified excessive green, Otsu's method, and the Hough transform were combined to find crop rows in a field, and dynamic extrinsic camera calibration and PID-controllers were used to make the UAV follow the detected crop rows. These methods can be used to support GPS-based navigation, or navigation based on ultra-wideband beacons (UWB, see below).

2.3 Hardware enhancement for swarm operations

We have chosen to exploit small and light UAVs for the mapping operations, as they can quickly reach any area of the field and monitor from close-by the presence of weeds. UAV research is a hot topic to date, pushed by the huge development of commercial flying drones, mainly thanks to the establishment of multi-rotor helicopters bringing to the consumer and industrial market stable and easily controllable platforms. However, to date UAVs are usually not conceived for group operation, and hardware adaptations are required to have UAVs communicate with each other and coordinate their operations. Additionally, if we consider autonomous flight with on-board sensing, research is still ongoing due to the size and payload constraints associated with aerial vehicles, as well as to the short battery lifetime [13, 22]. Specific control issues emerge for multi-robot settings, which render approaches with individual robot labelling impractical due to the exponential explosion of the state space, and call for low-dimensional abstractions of the group [17]. Additionally, specific sensory systems are required for collision-free flight and networked operations [7, 22]. In summary, several state-of-the-art technologies need to be integrated in a single platform to support swarm operations [29].

Within SAGA, hardware development to enable swarm operation will start from the PrecisionScout UAV platform (see Fig. 1 right), which is developed and produced by Avular B.V. in the Netherlands.[3] The PrecisionScout is an industrial-grade quadcopter with four motors and is able to fly up to 30 minutes on a single charge. The system is designed for inspection tasks where a high level of accuracy and safety is required. Key features include a triple redundant autopilot, five inertial measurement units (IMUs) and RTK-GPS. The location and orientation data will be synchronized with the imagery from the RGB camera, and the corresponding object detections/semantic segmentation. The payload itself is modular and the components are separated from the flight-critical systems, making it particularly safe for the development of real-time vision applications.

The standard PrecisionScout needs to be equipped with several additional hardware modules as well as software communication protocols. The hardware modules include radio-communication between multiple UAVs, based on UWB technology, which will provide at the same time self-localisation with respect to stationary beacons and communication abilities between UAVs.

[3] Avular is an SME partner of the SAGA experiment consortium (`http://avular.com`).

Additionally, the PrecisionScout must be enhanced with onboard vision and processing power so as to run the monitoring and motion algorithms. A design based on the Nvidia Jetson[4] will be developed allowing to use the same processor for both machine vision and motion control.

3 Baseline simulation of collective monitoring

Field monitoring is a fundamental activity in weed control. It consists of patrolling the field and detecting the weed presence and location. This activity is generally supported by absolute positioning systems (e.g., RTK-GPS) which allows geofencing and planning of the optimal path. The most common approach is a "sweeping" strategy, in which a ground or aerial vehicle follows a zigzag course. With multiple vehicles, the field can be decomposed in non-overlapping areas to be assigned to different UAVs [16]. In agricultural applications, it is often the case that coverage strategies allow to capture large amounts of images to be stitched together and analysed offline [28]. Clearly, these strategies do not provide robustness against failure of UAVs within the group, neither do they deal optimally with high error-detection rates. Indeed, *a priori* path planning and *a posteriori* analysis do not allow to adapt the monitoring strategy to the actual weed distribution and to exploit online visual processing to influence the field coverage. Within SAGA, we aim to produce a completely decentralised solution that exploits online visual feedback to direct the individual search strategy. In this section, we introduce a weed monitoring model and multi-agent simulations developed to quickly test different decentralised strategies.

3.1 Weed monitoring model

We consider an abstract scenario in which a square field of side L needs to be monitored for the presence of weeds. The field is virtually divided in square cells of side ℓ, for a total of L/ℓ cells per side, and each cell i can contain one or more weed units, resulting in the weed density ρ_i. We consider here N_w units that are distributed either uniformly in the field, or heterogeneously in N_p patches, where each patch p is obtained as a gaussian spread of items around the patch center $\mathbf{x}_p$ (standard deviation, σ_p, see Fig. 2, left column).

Each cell can be visited by a UAV—hereafter, agent—several times. At each visit $k > 0$, an agent a inspects the cell i for τ_v seconds and iteratively updates the locally estimated weed density $\hat{\rho}_{i,a}$ as follows:

$$\hat{\rho}_{i,a}(k+1) = (1-\phi_w)\hat{\rho}_{i,a}(k) + \phi_w \rho_i, \quad 0 \leq \phi_w \leq 1, \quad \hat{\rho}_{i,a}(0) = 0, \qquad (1)$$

[4] `http://www.nvidia.com/object/embedded-systems.html`.

where ϕ_w represents the percentage of weed that can be correctly detected in one visit: when $\phi_w = 1$ there is no detection error and one visit is sufficient, but when $\phi_w < 1$ more than one visit is necessary. The exponential average models detection from multiple visits as being independent from each other. At each visit $k > 0$, the agent a also computes the detection improvement:

$$\delta_{i,a}(k) = \frac{\hat{\rho}_{i,a}(k) - \hat{\rho}_{i,a}(k-1)}{\hat{\rho}_{i,a}(k)}, \tag{2}$$

which can be employed to label cells as completely monitored when $\delta_{i,a} \approx 0$, or still requiring additional visits.

For evaluation purposes, we compute the globally estimated weed density $\hat{\rho}_i$ of cell i by aggregating information from multiple agents, in a similar way as in equation (1). Additionally, we record the number of visits κ_i that each cell i receives. We consider the field completely covered and correctly inspected when $\forall i,\ \kappa_i > 0 \wedge \hat{\rho}_i = \rho_i$. We evaluate the efficiency of the monitoring activities by looking at the time t_c in which the field is first completely covered, and at the time t_w in which all weed items are correctly detected.

3.2 Baseline collective monitoring strategy

The division of the field in cells allows to simplify the motion strategy of each agent, and to ensure that no two agents inspect the same cell at the same time. We assume here a simple collision-free model in which agents are treated as point-mass particles with maximum speed v. Hence, the monitoring strategy reduces to the decision on which field cell to visit next.

As a baseline approach, we implement a random-walk-like strategy in which each agent a decides the next cell to visit according to a 2D gaussian distribution. More specifically, the likelihood to choose cell i by agent a is computed as follows:

$$F_a(i, j; \sigma_j, \gamma_i) = \gamma_i e^{\frac{-d_{ij}^2}{2\sigma_j^2}}, \quad \sigma_j = \frac{\hat{\sigma}}{1 + \hat{\rho}_{j,a}}, \quad \gamma_i = \begin{cases} 1 & \kappa_i = 0 \\ \delta_{i,a} & \kappa_i > 0 \end{cases}, \tag{3}$$

where d_{ij} is the Euclidean distance of cell i from the current cell j, and $\hat{\sigma}$ represents the base spread of the gaussian function. Given the likelihood value for each cell i, a roulette-wheel selection is performed to choose the next cell to visit. In this process, the current cell is excluded, as well as the cells targeted by other agents, which are available thanks to agent-agent communication.[5] By choosing cells according to equation (3), we ensure local exploration thanks to the gaussian spread, we promote longer displacements when the locally estimated weed density $\hat{\rho}_{j,a}$ is low (i.e., high values of σ_j), and we scale

[5] We assume here for simplicity a fully connected communication network among agents.

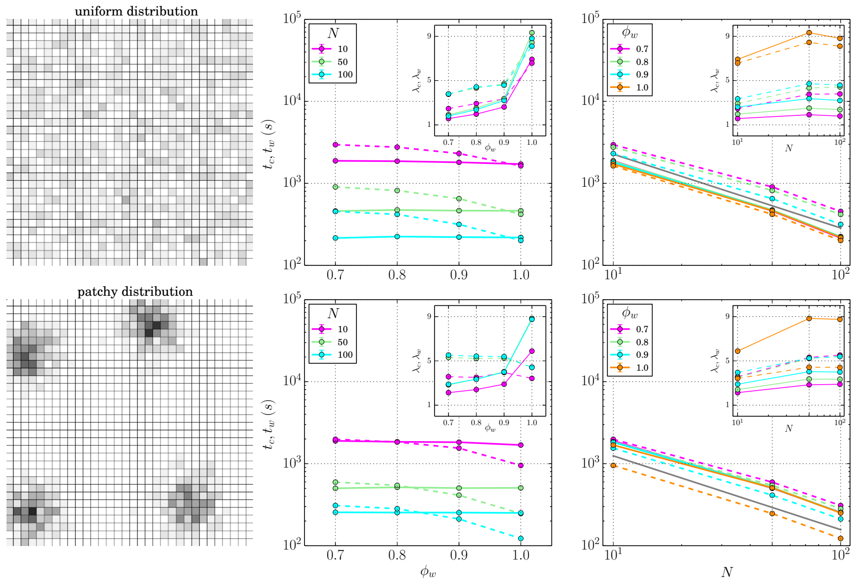

Fig. 2 Results of the baseline collective monitoring strategy for uniform (top) or patchy (bottom) weed distribution. Left: example density map of weed distribution, with darker areas corresponding to higher weed density. Center: Average value for the coverage time t_c (solid lines) and for the monitoring time t_w (dashed lines) plotted against ϕ_w, for various values of N. Right: Scaling of t_c (solid lines) and t_w (dashed lines) with the group size N. The black solid line is a guide for the eye corresponding to a power-law scaling $t \propto N^{-0.9}$. Insets: relative performance computed against the optimal sweeping behaviour. Statistical error bars are not visible on the graph scale.

the likelihood according to the latest detection improvement $\delta_{i,a}$, which goes to zero the more the estimated weed density approaches the real value, so as to avoid to often revisit the same cells. To summarise, the above strategy implements an isotropic random walk, giving lower importance to areas that have already been sufficiently covered. Note that this baseline strategy does not exploit agent-agent interactions, apart from excluding those cells that are already targeted by some other agent. Hence, much improvement is expected by the introduction of feedback mechanisms among agents.

For comparison, we developed a sweeping strategy in which a single agent $\hat{a}$ covers the whole field by moving through adjacent cells every time the detection improvement $\delta_{j,\hat{a}}$ on the current cell j falls to zero. We divide the coverage time $t_c^{\hat{a}}$ and the monitoring time $t_w^{\hat{a}}$ by the group size N, so to obtain the optimal performance $t_c^\star = t_c^{\hat{a}}/N$ and $t_w^\star = t_w^{\hat{a}}/N$ of a group implementing the sweeping strategy on a field partitioned in N non-overlapping areas. As mentioned above, the sweeping strategy—although optimal from the efficiency point of view—is not resilient and robust against failures, hence the motivation to develop a collective monitoring system.

3.3 Experimental results

Given the system described above, we have performed preliminary investigations to understand the influence of the different parameters on the global outcome. We vary the group size $N \in \{10, 50, 100\}$ and the weed detection rate $\phi_w \in \{0.7, 0.8, 0.9, 1.0\}$, and for each configuration we execute 200 evaluation runs in randomly generated fields with either the uniform or the patchy weed distribution. We observe that the coverage time t_c is independent of the weed detection rate for both uniform and patchy weed distribution (solid lines in the center plots of Fig. 2). This is expected given that the choice to visit new cells is not affected by ϕ_w. The average values of t_c are also similar for uniform and patchy distributions, as coverage requires to visit every cell in the field at least once. What changes significantly is the course of t_w (dashed lines in Fig. 2), which is decreasing for increasing values of ϕ_w, and above all presents lower values for the patchy weed distribution. Indeed, for high values of ϕ_w, only few visits are required per cell to completely inspect it (at most 2 visits per agent when $\phi_w = 1$), and this has a positive impact on reducing the detection time: in the uniform distribution case, t_w becomes comparable to t_c, as weeds can be found anywhere in the field; in the patchy distribution case, t_w gets significantly lower as weed patches are completely detected before the entire field is fully covered.

For what concerns the scaling with the group size N, it is possible to appreciate a power-law decay $t \propto N^\alpha$ for both uniform and patchy weed distribution, with exponent $\alpha \approx -0.9$, not too distant from the ideal case of $\alpha = -1$ (right plots in Fig. 2). This confirms that the provided solution—although improvable exploiting agent-agent interactions—scales very well with the group size. The performance relative to the optimal weeding strategy is shown in the insets, where $\lambda_c = t_c/t_c^\star$ and $\lambda_w = t_w/t_w^\star$ are plotted. It is possible to notice that the collective monitoring strategy is in general slower by a factor of 2 to 9, with best performance for low values of ϕ_w, especially for the coverage time, and for the monitoring time in the uniform distribution. For the patchy distribution, monitoring is 3 to 5 times slower than the optimal strategy, but performance slightly improves for $\phi_w = 1$.

4 Conclusions

In this paper, we have presented the SAGA concept and the roadmap it implements to bring swarm robotics into the field. We have also proposed an abstract model for weed monitoring and preliminary results exploiting a simple random walk strategy, which constitute a baseline against wich to test improved collective monitoring approaches. The baseline monitoring strategy is efficient against a patchy weed distribution, deals well with low rates of weed detection and present good scalability with the group size. It exploits multiple visits from different agents to obtain a complete monitoring. Given the absence of interaction among agents however, certain cells may be largely over-sampled, while others may receive insufficient attention hence requiring longer time to be monitored. Future work within the SAGA experiment will be dedicated to the engineering of a suitable strategy that minimises the gap with the optimal one, and that at the same time guarantees properties like resilience, robustness and scalability. Validation of the abstract model for weed monitoring with field experiments will be a key issue.

With the SAGA experiment, our goal is not only to demonstrate the technical feasibility of a swarm robotics approach to precision farming, but also to evaluate its potential economic impact. Indeed, one of the tenets of the swarm robotics approach is the usage of a large number of small and relatively simple robots, as opposed to large and expensive machines. Verifying the economic value of the swarm robotics approach in a practical application scenario is important for future developments of the field. We intend to use the knowledge gained and the results of the experiments to evaluate the economic advantages and drawbacks of a swarm robotics approach to precision farming. Weeding is actually a complex problem that is associated with potential yield loss and high labour costs. Our assessment will therefore include factors related to increased crop yield, reduction of labour cost, operation efficiency, potential miniaturisation/optimisation of robotic components, flexibility/reusability of solutions and size scalability.

Although spraying or other forms of weed removal (either from UAVs or ground vehicles) are not considered within SAGA, the potential impact of swarm robotics for agricultural applications will be fully unleashed when a complete solution can be delivered. Future developments should hence take into account not only decentralised sensing, but also parallel and collaborative approaches to weed control. In this way, it will be possible to put forward the relevance of swarm robotics also for other application domains.

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