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RESEARCH ARTICLE

# Optimized Offline-Coverage Path Planning Algorithm for Multi-Robot for Weeding in Paddy Fields

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**ABSTRACT** The coverage path planning (CPP) algorithms play a key role in autonomous robot applications, making area coverage operations efficient and cost-effective. The extension of coverage path planning algorithms to multi-robot operation is still widely unveiled despite the cyclical nature of agricultural operations, i.e., comprising repeated actions. The problem of coverage path planning for multi-robot operations is addressed in this paper. The three possible forms of multi-robot coverage algorithms evolved from the basic single-robot coverage algorithm based on the elementary trapezoidal method or zig-zag movements. Furthermore, an optimized coverage path planning algorithm for multiple in-row robots meant to control the weeding in an agricultural field is proposed. The parameters of the agricultural field are supposed to be known upfront, opening the application of an offline planning algorithm. The proposed algorithm stands tall in terms of distance covered with no repeated coverage compared with other possible solutions, nearing the results of single robot coverage (for which the planning is trivially simpler and there is no coverage repetition). Online adjustments in the multi-robot area coverage are also considered, and the proposed algorithm proves to be effective in simulation in this respect as well. The quantitative evaluation proves that, in the proposed algorithm with a team size of 15($n = 15$), the average distance consumed by each robot to cover the field taken for the study is only 65% of that of the other two algorithms. Also shows increase in the team size (n) leads to a decrease in consumption. This algorithm provides a solution for the autonomous operation of multi-robots to cover the fields with static obstacles at a regular pattern which is a common demand of many agricultural processes.

**INDEX TERMS** Coverage path planning, multi-robot path planning, agricultural robots, weeding robots, autonomous robots.

## I. INTRODUCTION

Paddy cultivation under the system of rice intensification(SRI) methods, compared to traditional methods of cultivation, improves yields if correct weed control methods are followed [1]. For an SRI method, the weed growth is maximized when the field is maximally exposed to sunlight, thus inducing regular gaps between plants and, hence, the plants are regularly deployed in rows and columns. Conventional methods of weed control, or even specific methods for SRI paddy fields, are either expensive or heavily reliant on chemicals or solutions that are not easily available, thus

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leading the farmers to avoid this favorable type of cultivation. Even though Mulching methods [1] can be applied in these cases despite their practical difficulties, autonomous robots [2]operating with a coverage algorithm are considered the future of farming. In the literature, single robot applications are usually considered for the automation of the weed control process, while the extension to multiple robots operating as a team and covering the field of interest is still an open issue. Indeed, the coverage of fields with obstacles in a pattern is a general problem in slurry fields for the cultivation of millets and grains, but also in oil palm, dates, and coconut farming [3], [4], [5], [6]. As such, it is still performed with single-robot approaches leaving few, while a multi-robot approach for weed clearance will be beneficial for evident reasons (e.g., reduction of coverage time due to workload division, consistency in the coverage process, and tangible increase in robustness even in the presence of few robot failures). SRI methods of paddy cultivation change according to the specificity of the area, which bears remarkable differences around the globe. For example, the solution developed in [7] builds around a specialized weeding robot for paddy fields using the Korean fields peculiarities, which has plants in rows and columns with a distance of 30cm between rows and 15cm between plants in the rows. When considering plants as static obstacles, the fields become the areas with static obstacles in a regular pattern. For instance, the papers [8], [9], [10], [11] deal with weeding in paddy fields inspired by integrated farming with natural ducks and paddy. These solutions cover the feasibility study of their weeding robots, considering their developments and capabilities, the possible damage to the plants, and, more importantly, the path planning for the robots. What is of major interest to this paper is that the mentioned publications show the demand for multi-robot coordination and path-planning algorithms, which are not covered. Based on our previous work [2], where the design of a weeding in-row robot for the paddy field under the SRI method of cultivation has been presented (i.e., coverage of a field with static obstacles at a regular pattern), The authors present here our proposal for offline coverage path planning for a team of weeding robots, a still open problem of interest to many research groups around the world as testified by the mentioned literature.On the other hand, the main issue that still hinders the wide application of multi-agent systems for this application scenario is the needfor an efficient and lightweight optimal path planning algorithm for the team of multiple in-row mini robotsthat have to cover the paddy field under the SRI method of cultivation, and search for it becomes our objective of the study.

The rest of the paper is organized as follows. Section II describes the literature work. The detailed description and analysis of the algorithm are discussed in Section III, while its performances are assessed in Section IV. We conclude the discussion in Section V, together with an outlook of future improvements

## II. LITERATURE WORK

For a single autonomous vehicle, the coverage path planning (CPP) algorithm aims to find a suitable path that entirely covers the field or the region of interest (ROI)while avoiding all the obstacles in the field. Notable solutions have been conceived for automated harvesters [12], [13], lawnmowers [14], [15], window cleaning [16], or vacuum cleaning [17] robots, all dealing with a bi-dimensional (2D) ROI with an even and plain motion surface. Extensions to the 3D ROI of such solutions, e.g., for painting [18] or underwater structure inspection [19], have been already provided. Of course, the 3D ROI problems are more challenging than 2D, albeit the former can be decomposed into a sequence of 2D problems [20]. Efficient CPP solutions work either online [21], [22], [23], [24] or offline [25] depending on the availability or absence of a sufficient level of information about the field to be covered. In particular, offline algorithms work on the assumption that all the ROI information is available, albeit occasionally this may not be true. On the other hand, online algorithms can collect information from the field using the available sensors [12], [13]. When obstacles come into play, it is possible to subdivide the ROI using different decomposition techniques to be applied online [26], [27], [28].

The known work on the CPP algorithm has the following basic 3-stages: road map generation, path planning, and continuous refinement. For an offline algorithm, the road map generation and the path planning will produce a complete solution. In general, an online solution is considered when there is uncertainty in the knowledge of the environment, i.e., the road map creation and the path planning will be uncertain and will ask for updates in due course. Therefore, the validation and the optimization of the parameters will radically differ. Indeed, the parameters of the offline CPP algorithm are basically the total travel distance, the total number of turns, the percentage of coverage, and the percentage of the repeated coverage area (i.e., non-backtracking). In the case of an online solution, these parameters are enlarged to include, e.g., the accuracy of the map creation and/or the road map generation, thus being closer to unknown areas exploration and/or update of a known dynamic map. In such a case, exploration time and computation time reduction as well as the collaborative exploration strategies are the main issues to cope with. Thus, a sensor-based (or learning-based) approach with an on-purpose cost function definition for coverage (or exploration)is usually considered [29]. Due to such limitations and complexity increase, online multi-robot CPP algorithms are usually not the choice for a static environment like the typical agricultural practical solutions, thus the offline approaches are the preferred choices.

Besides the mentioned different approaches, single robot path planning methods have differences also in the environment representation details, e.g., map and/or graph-based approaches to pre-estimate the costs between any two points in the environment [30], [31] or to detect coverage points pattern [32], [33], and on the adopted path planning solver, e.g., game theory-based approaches to avoid an obstacle or AI-based approaches for learning [34], [35]and grid-based approaches for a pattern of coverage points [32], [33]. Some bio-inspired approaches are also available [36], which however do not fall in the path planning problem as tackled in this paper. In the field of agriculture, the most popular and effective solutions rely on basic coverage planning methods [37], [38], [39], like zig-zag or trapezoidal patterns [25], [26], [40], inward, outward, or shift spirals [41], [42], [43], random walk [43], [44] or wall following [43]. The path synthesis in this context is obtained with classical path synthesis methods [37], [38], [39], albeit multi-objective optimization techniques are also applied [45], [46]. However, these solutions are based on the basic trapezoidal [47] or a combination of the previously discussed basic methods [48]. Despite the remarkable differences between the mentioned approaches, i.e., online vs. offline, the different decomposition techniques adopted, i.e., map, graph, grid, or occupancy cells, and the optimal solver considered, e.g., AI-based or game theoretic, all the reported literature solutions for single autonomous agents rely on a combination of the aforementioned basic methods, i.e., trapezoidal, zig-zag or similar patterns. Even though the problem has been investigated from many perspectives and different types of solutions are readily available, the multi-robot dimension for offline CPP algorithm is still not well investigated. In such a case, the problem turns out to be highly constrained and with stringent requirements ensuing from the nature of the cultivation. As can be expected, many multi-robot coverage algorithms come from the evolution of single-robot approaches [41], [42], [49], with the adoption of additional techniques to deal with the increased complexity, such as the boustrophedon decomposition [26] or spanning trees [31], [39]. Trivially, the CPP complexity increases for multi-robots since the presence of moving robots is perceived as obstacles, deadlock configurations among robots are always an issue, and task scheduling to orchestrate each robot in the team is needed [28]. Nonetheless, there is an obvious reduction of coverage time due to workload division, while consistency in the coverage process is increased as well as a tangible improvement in robustness even in the presence of few robot failures [27]. This paper is mainly inspired by the work of [42] to design the proposed multi-robot coverage path planning algorithm.In that work, the authors reduce the number of turns while covering the ROI by solving the single robot CPP with spanning tree coverage, which is based on the improved ant colony optimization algorithm and depth-first search algorithm. The ensuing improved ant colony-based spanning tree covers the ROI with minimum turns. The extension to the multi-robot CPP is carried out by dividing the area using the DARP (Divide Areas based on Robots' Initial Positions) algorithm and considering each non-overlapping sub-area to be covered by the single robot. To further reduce the number of turns, the end nodes are exchanged between the sub-areas. Besides the evident limits in approaching the problems with sub-areas (which surely won't lead to optimal planning), robustness against robot failures cannot be guaranteed. Also, the DARP-based division of areas relies on the availability of a robot for each sub-area, which is hardly satisfied in practical applications. The proposed multi-robot CPP algorithm addresses and solves these issues, still retaining the properties of the CPP algorithm, i.e., the minimum coverage length and a minimum number of turns, thus making it a perfect benchmark to validate our solution. The other related work in [50], discusses the multi-robot CPP algorithm with heterogeneous properties of the robots, like different turning radii, different coverage sizes, etc., when handling different coverage sizes of robots, then largest of all is the extra space required to make the turn operation for shifting row, which may not be available in reality for the agriculture fields. Here the multi-robot CPP algorithm has evolved from basic trapezoidal which is better in terms of the number of turn operations taken when compared to the spanning tree as earlier. It also loses the property of consistency in coverage similar to an another work in [51]. In [51], discussed the CPP algorithm for multi-robot based on spanning tree handle the task of coverage in the way of single-robot and losses the consistency in coverage as mentioned earlier.There is a different approach in farmland coverage in using the non-interest part of field for taking turn by an Ariel robots [52] and similarly another Ariel solution [53] for optimization of agriculture management tasks with a cost function by reducing the number of turns taken. Another similar approach to the agriculture task management is discussed in [54], whereasingle robot online path planning based on the boustrophedon coverage path (BCP) planning algorithm for an autonomous weed mowing robot named Cowbot is presented.This solution reduces the length coverage by effectively visiting only the sub-regions in need of mowing. The way the robot departs from the base path to the sub-region, and then joins back, is based on two variants of the algorithm, named JUMPand SNAKE, respectively. Moreover, even though many solutions are available today, there is a substantial lack of analysis and proposals for offline coverage with static obstacles at a regular pattern, which is, instead, the case for the large majority of agricultural fields, and the focus of this paper. Therefore, the authors present here a solution for the challenging problem of offline coverage path planning synthesis considering multiple robots operating together as a team. In the algorithm synthesis, we will make explicit use of the fact that paddy fields are structured without uneven surfaces and, hence, can be considered 2D fields. In particular, using an offline CPP algorithm for multi-robot, this paper proposes a 3-stage process dubbed offline road map generation, discrete planning, and continuous refinement, respectively, which defines the decentralized path planning solution with very minimal data transfer between robots. The discrete planning allows the online adjustment of the size of the team of robots, whose continuous refinement at the synchronous field locations is an essential component.The energy utilized by the team of robots for the coverage task is a further factor that is optimized in the offline CPP algorithm. The energy consumption is mainly due to the robot's motions, hence including the total distance traveled and the total turns taken during the coverage task. Without loss of descriptive potentialities, the least turn-taking method is selected, with simple motion as a base method to develop the multi-robot algorithm, therefore optimizing the total distance, which is, in turn, a function of the energy utilized for the task of coverage. By remapping the energy consumption onto the total traveled distance and the total number of turns, the comparisons with existing methods are readily available.

The proposed solution for coverage path planning can be applied to any size of the field, any shape, and any number of fields satisfying the assumptions. When this is not possible, the extension to arbitrary field shape is developed using decompositions in sub-areas, which in turn has to satisfy the assumptions, as will be explained later in the paper. It has to be noted that the main distinctive features of the proposed distributed solution with respect to the state of the art are a) the simplicity of the path synthesis derived from the trapezoidal approach, b) the possibility to change dynamically and in a smooth way the number of agents in the team, c) the generation of paths that are equivalent for all the agents in the team with respect to the power consumption.

Finally, the authors would like to point out that the application of the proposed solution in actual agricultural scenarios is immediate, mainly due to the abstraction proposed in the paper. Actual experimental results will be mainly affected by the need for accurate and robust localization, mainly fusing data from different sources, e.g., odometer and GPS, to estimate the positions of the robots in the team as well as by the effectiveness of the motion controller applied. However, numerous research works for the localization of a single robot and its extension to multi-robots have been provided in recent years [55], using centralized or distributed approaches [56], as well as decentralized approaches [57], [58], [59]. For multi-robot localization, landmarks attached to mobile platforms are usually adopted for performance improvement and robustness. In [60], a data fusion algorithm based on received signal strength (RSS) and two-way time-of-flight (ToF) measurements are used to increase the range-based localization in an indoor environment. In [61], localization and tracking of moving targets based on the fusion of various sensor data is also considered. In [62], approaches with quick response (QR) code landmark recognition have been proposed. Since this paper does not deal with the estimation problem neither of the robot locations nor with the definition of a novel motion controller but, rather, with the path planning, the authors do believe that experimental evidence is not strictly needed, being outside of the scope of this paper.

## III. MATERIALS AND METHODS

Considering the weed growth explicitly, the SRI field has the following requirements:

1. **Requirement 1**: Weed control has to be performed every 20 days, ideally three times for one cultivation;
2. **Requirement 2**: Each weeding has to be performed on all four sides of the plants.

When autonomous robots are considered, the second requirement imposes two laps of weeding, where each lap covers two sides of the plant and has to start at two perpendicular sides of the field, hence combining all four sides. Moreover, the robot should avoid damaging paddy plants, so treat them as static obstacles; instead, all the other robots in the team are treated as dynamic obstacles.

To tackle this challenging problem and to derive the coverage algorithm, these assumptions should be made explicit:

1. **Assumption 1**: The field is well structured, without unknown static or dynamic obstacles (apart from the mentioned plants and for the other vehicles);
2. **Assumption 2**: Plants are rooted in columns and rows with fixed distance (typically, the distance between the plants and/or rows for weed fields is $d_f = 30$ cm);
3. **Assumption 3**: The performer of the weeding robot will do weeding for the coverage length;
4. **Assumption 4**: Robot coverage size is less than the spacing between rows.

Notice that **Assumption** 3 states that the main focus is robot path planning and navigation, while the weeding process per se is assumed to be implemented automatically by the robot along the trajectory. Finally, noticed that the width of the coverage for each robot is adjusted to compensate for plant growth.

To introduce the proposed algorithm, the authors adopt a constructive approach, proposing in detail the pros and cons of the existing solutions and their extension to the multi-robot CPP algorithm. In the proposed analysis, the authors will consider the SRI paddy field as the ROI. The four key basic algorithms used for single robot approaches, which will be described in detail in what follows, are reported in Fig. 1. The single robot coverage using the basic trapezoidal method is reported in Fig. 1(a): this simple method covers the region using back and forth motions. It can be applied to any even-sided or rectangular field with or without field decomposition [25], [26], [40]. Fig. 1(b) shows the inward-spiral method that covers the field using spiral paths: the robot starts close to the outer boundary and moves towards the inner part of the fields [43], [63], [64]. Similarly, Fig. 1(c) shows the outward spiral, which is the same as the previous, one but with an opposite motion direction [63], [64], [65]. Probably, the most desirable feature of the spiral approach is that it can be used with simple wall-following like robot motion controllers. Instead, the main drawback is that the robot obviously needs extra motion to reach or to leave the inner part of the ROI, which leads to extra costs and, thus, should be avoided [66]. The direction of rotation is maintained as either clock-wise or counter clock-wise as shown in Fig. 1(b) and Fig. 1(c): combining both directions and switching the direction at the boundaries from one another,

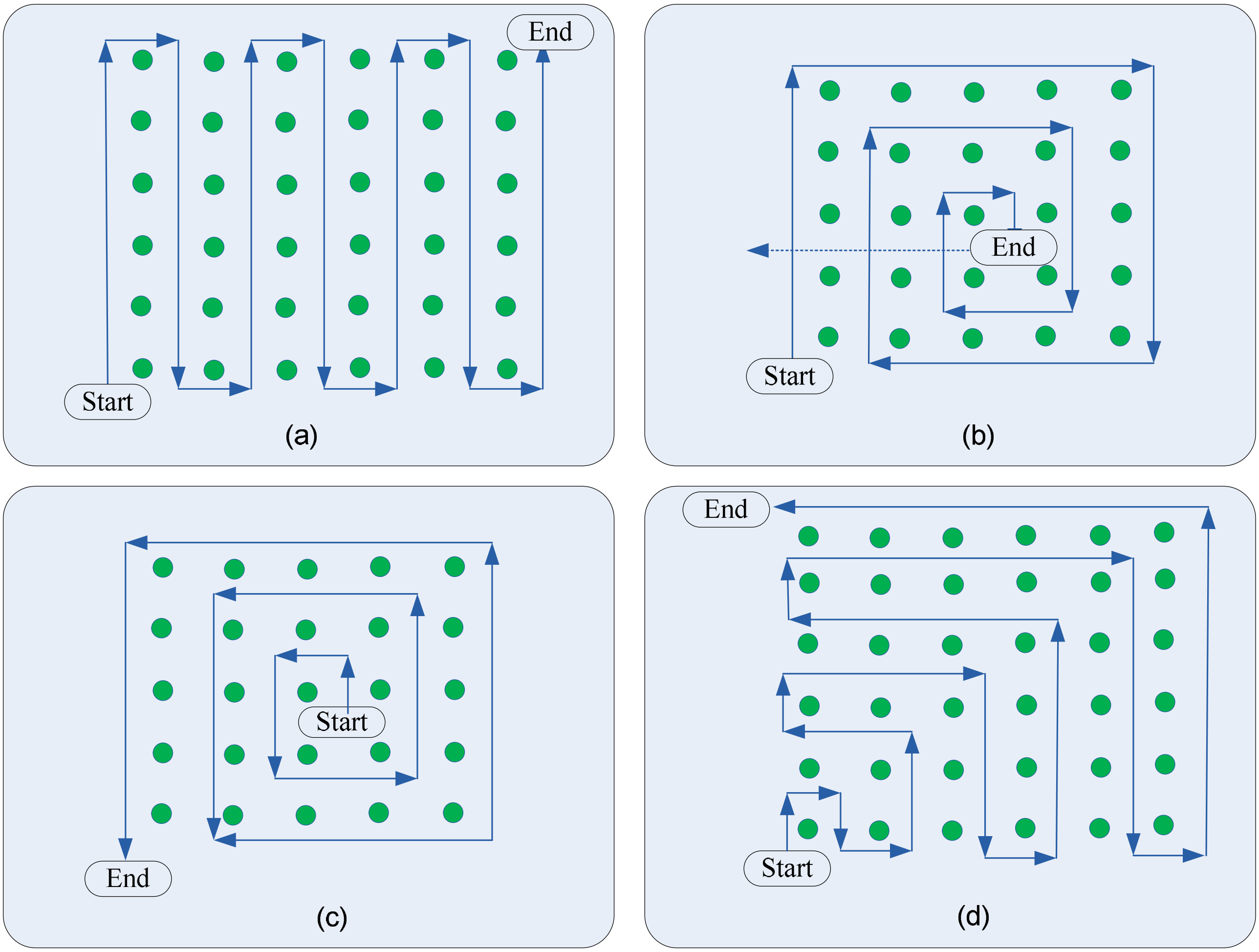


**FIGURE 1.** **Basic methods used for single robot CPP (a) using single robot trapezoidal coverage, (b) using inward-spiral coverage, (c) using outward-spiral coverage, and (d) using switched-spiral coverage.**

yields another variant, dubbed switched spiral [41], [42] and depicted in Fig. 1(d).In this case, the CPP algorithm starts and ends at a point near to boundaries of the ROI, similar to the trapezoidal method. This feature makes the switched spiral be considered along with the trapezoidal method as an option for developing a multi-robot CPP algorithm since it avoids the extra robot motion to or from the center of the spiral.

To compare the trapezoidal and the switched-spiral methods, the authors use an example field of 6 rows and six columns (Fig 2). To satisfy **Requirement 2**, the authors split the coverage into two laps: each lap takes, for the switched-spiral of Fig. 2(b) an overall traveling distance of $48d_f$ (See the definition of $d_f$ from **Assumption 2**) with 17 turns, instead of $48d_f$ with 12 turns for the trapezoidal method of Fig. 2(a). Overall, the number of turns is 34 for the switched-spiral and 24 for the trapezoidal. This is extremely relevant since an increased number of turns has a major impact on the cost of the coverage [27], especially in the slurry paddy field. Another advantage of the trapezoidal method is that it is suitable for rectangular or even-sided fields, while the switched spiral, in its classic application, is just suitable for square fields unless the total ROI is split into squared sub-areas.In such a case higher complexity and computation costs are obtained as well as an efficiency decrease induced by the extra maneuvers used for the robot motion between the subareas [42].

From the previous discussion, the trapezoidal method proves simpler and cheaper compared to the switched spiral, and hence, it is a good starting point for an extension to multi-robot operations. To satisfy **Requirement 2,** the coverage should be executed in two laps with the same CPP algorithm, notice that the two laps are consecutive and independent of each other, as aforementioned. Therefore, the effective extension to the multi-robot case can be carried out just considering a single lap, being the second straightforward and identical (as reported in Fig. 2).

The first issue to be tackled when a multi-robot extension is considered is related to the position of the robots in the team during the execution of the operation. Considering the selected trapezoidal approach, maintaining the position of the robot in the team for both the forward path and return

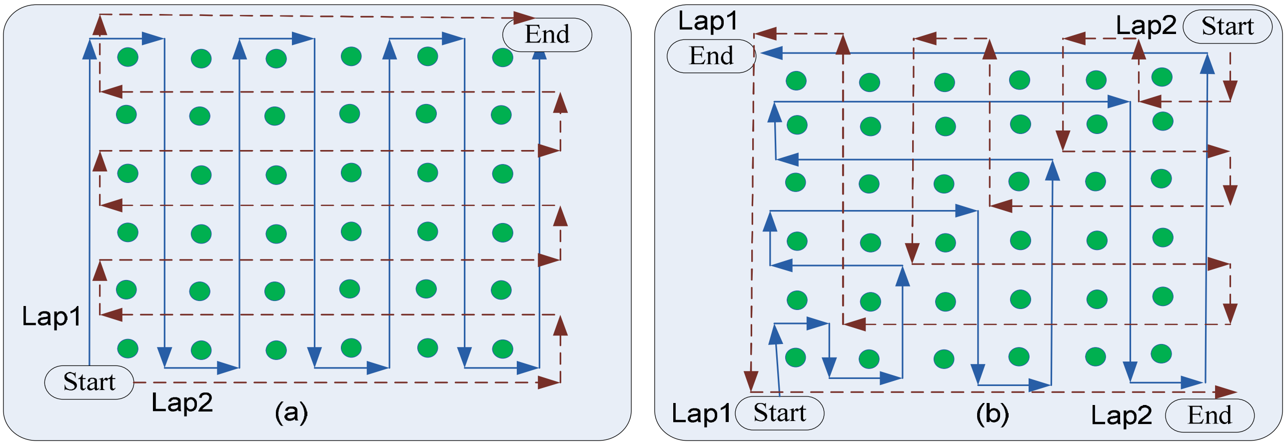


**FIGURE 2.** CPP for two laps with (a) trapezoidal coverage and (b) switched-spiral coverage.

path from the starting side gives one variant of the algorithm, which is shown in Fig. 3(a) and dubbed multi-robot trapezoidal (MRT) method. Instead, if the robots are allowed to change their positions(i.e., the first robot becomes the last if the order is set from left to right, as depicted in Fig. 3(b)), this gives another variant of the algorithm named position changing multi-robot trapezoidal (PCMRT) method.

Both the presented variants have a common disadvantage: the outer upper and lower rows are uselessly covered multiple times by multiple (possibly all) robots. Moreover, the path is not robust against slight variations in the desired velocity of any vehicle, i.e., the robots should be synchronized in the execution of the paths to avoid collisions by design. To account for these issues, we propose *non-overlapping path planning for multi-robots based on trapezoidal*(NOMRT). The proposed algorithm covers two sides of each plant for each lap, as shown in Fig. 4(a), and avoids possible collisions among the robots along all the paths, thus ensuring robustness by design (i.e., the paths do not overlap nor intersect).In this respect, NOMRT can be seen as an improved version of the PCMRT since the common distance covered by multiple robots to shift their positions among the different columns is removed. Another quite interesting property is that the distance traveled by each robot in the team is the same among any two (yellow lines) consecutive synchronization points of Fig. 4(a), thus enforcing a nominal equal depletion of the battery power for each robot. It has to be noted that the NOMRT has a periodic execution; that is, the portions of the overall path repeat with equal shapes, thus simplifying the coding and the execution of the path and enforcing its online execution.

Another important feature that makes the NOMRTalgorithm effective in the multi-robot scenario is that the number of robots in the team can be adjusted online as well as the team configuration along with the execution of the coverage by allowing the dynamic addition and deletion of units from the team, as shown in Fig. 4(b).

Indeed, the assumption that all the robots are available during the coverage process (hypothesized in Fig. 4(a)) is unrealistic due to maintenance operations, battery depletion, possible robot failures, or dynamic allocation of new robots. Also, when the field coverage is near completion, the number of robots required to complete the remaining work may be reduced to improve efficiency (more on this in Section IV).

Even though the NOMRT algorithm plans an optimized path, there is a need to limit the amount of off-task movements of the robots(i.e., movements that are not part of the coverage work, such as the field entry and exit operations, which may be more efficient given the location of the next field to cover).In general, all these cases influence the optimal team size in all possible directions during the executions of the algorithm. Therefore, the management of the team composition is enforced at every key point (i.e., the synchronization points of all robots, which are the end of each column in Fig. 4(a) and denoted with diagonal yellow lines) in the periodic structure of the algorithm. In such locations, the team may arbitrarily change size and configuration, still, the NOMRT maintains a periodic path structure. To show this fact, the authors use an example: consider the exemplifying scenario of Fig. 4(b): three robots (R1, R2, and R3) start from the lower left corner of the field. After a while, robot R2 leaves the field due to battery shortage; hence robot R3 switches to R2. Now, if no other robot is available, R1 and the new R2 may carry out the coverage; otherwise, if a new robot R3 is available, it may join the team, thus reforming a three-robot team to complete the field coverage. Notice that, in this way, the coverage is always guaranteed, while the number of robots in the team influences the time to accomplish the mission: as described next, the more robots, the less coverage time.

### A. ALGORITHM DESCRIPTION

The proposed NOMRT algorithm can be divided into a sequence of different parts, namely "Start", "Direction-1", "Direction-2", "Direction-3", …., "Direction-m"

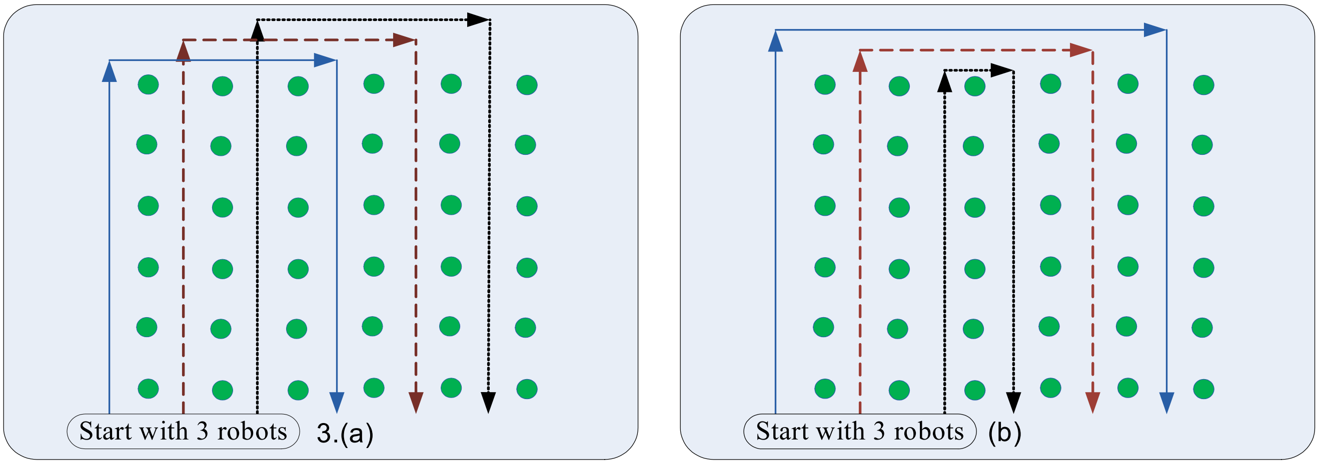


**FIGURE 3.** Two variants of multi-robot based on trapezoidal:(a) multi-robot trapezoidal (MRT) and (b) position changing multi-robot trapezoidal (PCMRT).

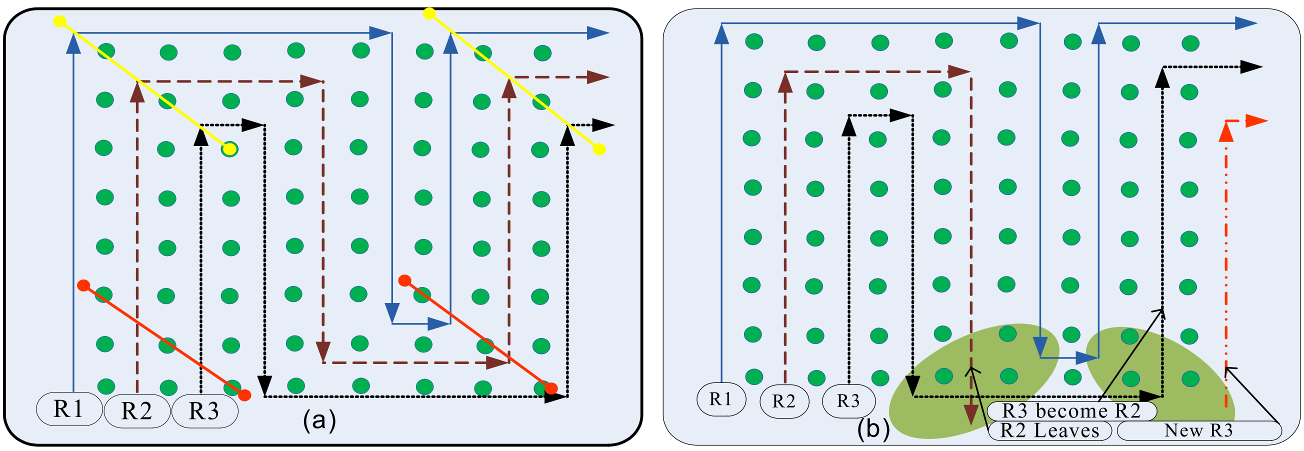


**FIGURE 4.** Non-Overlapping-multi-robot-trapezoidal (NOMRT) in (a) a basic scenario and (b) during a team reshaping.

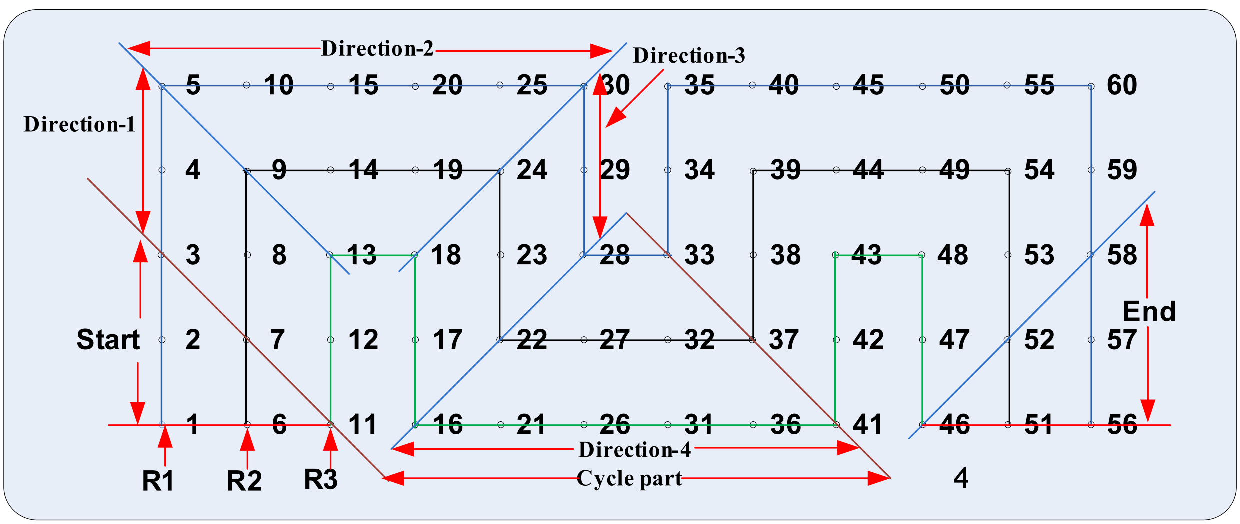


**FIGURE 5.** Different parts of the NOMRT algorithm.

and "End". In the example of Fig. 4, the four parts from "Direction-1" to "Direction-4" are repeated cyclically, while the remaining two, "Start" and "End", are non-repeating and manage the beginning and ending phases of the coverage path. Notice that in Fig. 5thepath is represented with a graph, whose locations are numbered for clarity: the edges between nodes represent the path the robots will cover between the node locations. Therefore, the plant can be considered to be placed in the center of the square, whose vertices are four neighboring nodes. As a consequence, each edge in the graph equals the distance between two plants in a column or between columns (i.e., the $\boldsymbol{d_f}$ Distance defined in Assumption 2). The traveled distance is hence measured in terms of an integer multiple of $\boldsymbol{d_f}$, which differs for each rice variety considered.

Let the number of the field rows be r, the number of the field columns be c, the number of available robots in the team be n, and the position of the robot in the team as $p \in \{1, \ldots, n\}$. Fig. 5 reports a case with $r = 5$, $c = 12$, and $n = 3$, and it will be considered as the reference for the following description. In the "Start" part of the algorithm, each robot reaches the first synchronization section (bottom leftmost diagonal line in Fig. 5), where the cycle part begins and the "Start" phase terminates consequently. Similarly, the "End" part of the algorithm is required for any leaving robot to complete its current column from the last synchronization section (bottom rightmost diagonal line in Fig. 5).

The overall distance for the $\boldsymbol{p}$-th robot of the team for the "Start" $\boldsymbol{d_{s,p}}$ and "End" $\boldsymbol{d_{e,p}}$ parts, respectively, is given by

$$d_{s,p} = d_{e,p} = d_f\,(n-p)\,. \tag{1}$$

As a consequence, the first robot (R1 in Fig. 5), which has $p = 1$, travels the longest path, while the last robot (R$n$ =R3 in Fig. 5) travels the shortest. After the "Start" part, the robots enter the cycle path, comprising "Direction-$m$", with $m$ odd, which is the same for each robot in the team and equal to

$$d_{m,p} = d_m = d_f\,(r-n)\,, \tag{2}$$

and "Direction-$l$", with $l$ even, which is different for each robot and split into two contributions: $l = 4k-2$ and $l = 4k$, with $k = 1, 2, \ldots$ an integer number, i.e.

$$d_{4k-2,p} = d_f\,[2\,(n-p)+1]\;\text{and} \tag{3a}$$
$$d_{4k,p} = d_f\,[2\,(p-1)+1]\,. \tag{3b}$$

It has to be noted that, using Eq.(3a & 3b), for any given k, $d_{4k-2,p} + d_{4k,p} = 2nd_f$, hence the length of the path given by "Direction-l" and "Direction-l + 2", for any given even l, is the same for any given robot. Therefore, using Eq.(1, 2, & 3), for a field as depicted in Fig. 5, the difference in the path length among the robots is only given by the "Start" $d_{s,p}$ and "End" $d_{e,p}$ parts.

It is worthwhile to note that, if the robots are allowed to exit from another side of the path (the right side of Fig. 5), all the robots would travel the same distance. For example, in Fig. 5, if R1 exits in position 58 instead of56, R2 in position 57 instead of 51, and R3 in position 56 instead of 46 (i.e., moving through different columns in the "End" part of the algorithm), the path lengths for all the robots are the same. Of course, this design choice is left to the field manager, and in the following, we will refer to Eq. (1) only.

Another major difference happens when $c$ is not an integer multiple of the number of robots $n$: in such a case, some robots exit the field from the right or the top. For example, by removing the last column in Fig. 5, robot R1 would leave the field from position 55. It is also noticed that necessarily $n \leq c$ to apply the described algorithm since a larger number of robots would not be useful. Instead, if $n > r$, the depicted algorithm is applied only to $r-1$ robots in the team, while $n-r+1$ will cover one column. Moreover, when $n = r$, the robots execute the "Start" and "End" maneuvers, while the other parts boil down to straight paths along the field rows.

Furthermore, given a certain number $n$ of robots, the number of columns that can be covered from "Direction-1" to "Direction-3" is $2n$. Therefore, after the cycle "Direction-1" to "Direction-3", if $c - 2n \geq 2n$, the same group of $n$ robots continues, otherwise, a number of $n'$ robots such that $c - 2n \geq 2n'$ continues in the coverage, while $n - n'$ robots leave the team. Considering the rows, as previously stated, it is necessary that $n \leq r-1$ for maximum efficiency of the algorithm since the algorithm performs better when the number of agents increases (as will be clear in Section IV). Following this simple evidence involving $c$, $r$, and $n$, the team can adjust its dimension offline or online in a distributed way. Moreover, notice that any robot in the team may leave the group, thus enforcing the maximum flexibility and, hence, opening to battery power savings and/or maintenance operation optimization approaches. Finally, this algorithm can also be applied to the non-rectangular field by dividing the field into possible rectangular smaller fields using decomposition techniques [26].

### B. PSEUDO-CODE OF PRIMARY STEPS

Fig.6 shows the pseudo-code describing the complete flow of the algorithm, which is divided into modules executed in sequence. The main feature of the algorithm is probably the fact that each robot broadcasts its status to all the team members through message exchange to provide decentralized knowledge and enable flexibility and scalability [67], [68]. The message broadcast contains the position of the robot, its battery status, and the current synchronization point the robot has reached. With this simple message exchange, each robot has a complete picture of the recent execution of the algorithm. Notice that the information exchange is extremely simple since the NOMRT is intrinsically safe, which in turn makes the algorithm extremely robust to communication failures. We left to future investigations the possibility of applying more sophisticated approaches based, e.g., on consensus or distributed control.

The three presented extensions to multi-robot systems, i.e., the MRT, the PCMRT, and the proposed NOMRT, stemming


**FIGURE 6.** Pseudo-code of the NOMRT algorithm.

from the trapezoidal method, are here tested. Since the number of turns taken by all three mentioned variants is the same, the overall distance can be used as the figure of merit for comparison. All three multi-robot variants, along with the basic trapezoidal algorithm for a single robot adopted as a baseline, are simulated using the graph support of MATLAB depicted in Fig. 7, describing a field size of $r = 8$ rows and $c = 12$ columns.

Start by analyzing in Fig. 7(a) the CPP for a single robot using the simple trapezoidal approach, starting its path at node 1, moving to node 8, then 16 and so hence and so forth. Fig. 7(b) shows the CPP instead using three robots with the MRT algorithm, considering that robots R1, R2, and R3 are starting their path at node 1, node 9, and node 17, respectively: all three robot paths are shown in different colors and different line-styles. Robot R1 starts at node 1, moves to node 8, then shifts the column from node 8 to 32 through nodes 16 and 24, then moves towards node 25 to cover that column, shifts the column again, and repeats the same pattern.

Robots R2 and R3 follow a similar column-based pattern, maintaining the same formation. It has to be noted that the end of each column corresponds to the synchronization lines

**TABLE 1. Comparison of the distance taken by three variants of multi-robot trapezoidal.**

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 10 | 15 |
|---|---|---|---|---|---|---|---|---|
| MRT | 1199 | 1256 | 1311 | 1364 | 1415 | 1464 | 1640 | 1815 |
| PCMRT | 1199 | 1256 | 1311 | 1364 | 1415 | 1464 | 1640 | 1815 |
| NOMRT | 1199 | 1198 | 1197 | 1196 | 1195 | 1194 | 1190 | 1185 |

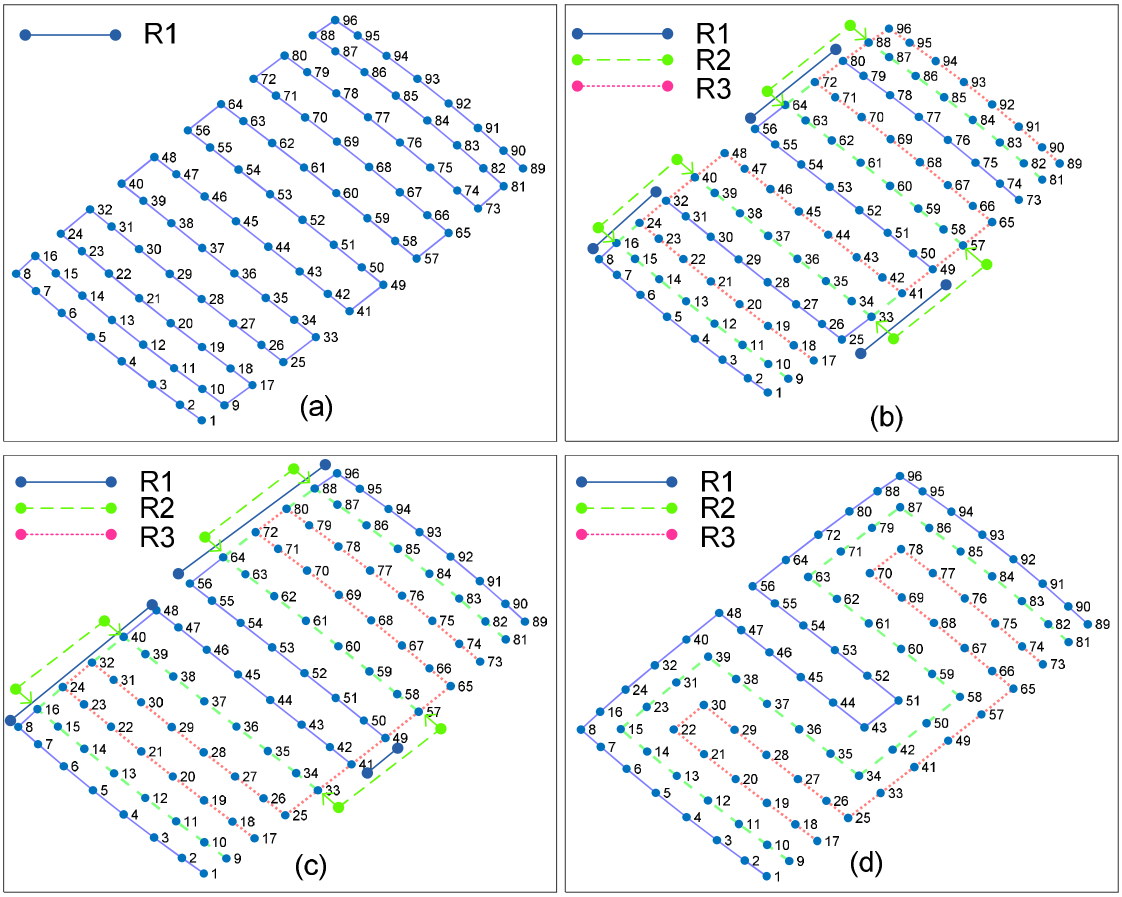


**FIGURE 7. Simulation results of the CPP using (a) single robot-trapezoidal, (b) MRT, (c) PCMRT and (d) NOMRT.**

for the team and that some portions of the paths, i.e., when the robots switch the columns, are uselessly in common, as mentioned. Fig. 7(c) depicts the CPP using the PCMRT algorithm for the same team of three robots, considering that the robots R1, R2, and R3 are starting their path at node 1, node 9, and node 17 and all the robots cover their respective columns, as in the MRT case. However, the column shifts happen differently: the innermost robot R3 (near the uncovered area) at node 24 moves just to the very next column available, which is node 32. Similarly, robot R2 moves from node 16 to node 40, which is next to the R3 position (at 32), while R1 moves from node 8 to the furthest uncovered column at node 48. Notice that some portions of the path are uselessly in common and that after two shifts, the distance covered by all the robots is the same, thus making the PCMRT very much like the MRT in terms of turns and distance traveled.

Finally, Fig. 7(d) shows the CPP using the NOMRT algorithm. The starting locations for the three robots are the same as the previous two cases, i.e., node 1, node 9, and node 17, respectively. However, in this case, only robot R1 covers the entire available column, while the other adapts the column cover based on their position in the team, as described in the previous section. The column shift happens as in the PCMRT;

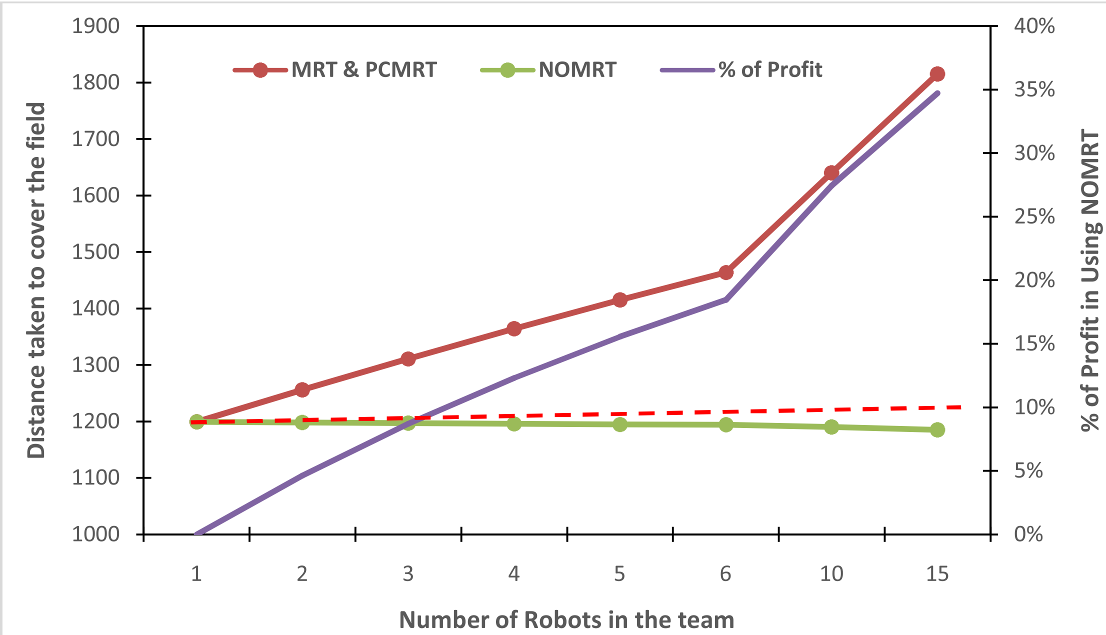


**FIGURE 8.** Comparison of three variants of the trapezoidal method, with different team sizes.

nonetheless, these maneuvers take place at different rows, thus removing the portions of the path in common.

## IV. RESULT AND DISCUSSION

For a quantitative evaluation, reported in Table 1, the overall traveled distance as a multiple of $d_f$ by a team of robots with $n \in \{1, 2, 3, 4, 5, 6, 10, 15\}$ acting in a field with $r = 20$ rows and $c = 60$ columns and using the MRT, the PCMRT, and NOMRT as planning algorithms.

It is evident how the NOMRT algorithm outperforms the other two solutions when the number of robots in the team increases. Moreover, it may be noticed that a steady improvement of the performance as a function of $n$, which is exactly the opposite of the other two algorithms, which perform the same in the selected example. This detrimental effect is mainly due to the presence of the uselessly covered paths for column switching. It is also noticed that from the study (ref Table 1.) when $n = 15$, MRT and PCMRT have an average traveled distance for each robot that is $121d_f$, while the NOMRT has $79d_f$ path length per robot, which means, consumes only (Also, in terms of battery power) 65% distance per robot that of the other two algorithms. In synthesis, the NOMRT is the only solution that can fully exploit an increasing number of robots in the team.

To further substantiate the comparison, the dashed red line in Fig. 8 reports the distance taken by a single robot with the baseline trapezoidal method. The NOMRT graph line is very near to the benchmark line and does not reduce efficiency in terms of distance in dividing the task by using multiple robots. The percentage of profit calculated on the entire team of robots is instead reported in the right-hand scale for the NOMRT compared to the other two solutions as a function of the number $n$ of the robots in the team. It is worthwhile to note that the optimality of the NOMRT algorithm is ensured by the trapezoidal path, on which it is built upon. Indeed, assuming that the trapezoidal path for a single robot covers all the plant sides without path overlaps and that each path segment is always on the side of at least one plant, it reaches the minimum length, thus it is optimal. Since the NOMRT inherits the same properties, it is optimal in the same sense.

To further analyze the NOMRT proposed solution, consider different scenarios. In particular, the objective of this additional analysis is to show the capability of NOMRT to change online, its team robot numbers while covering the field. As in the previous example, the locations the robots will move through are depicted with nodes, while each robot has a different color and a different line type for the path taken.

*Case I. (Team Size Reduction):* In the example of Fig. 9(a), we consider a field with $r = 8$, $c = 10$, and $n = 3$ with the constraints that the robot must enter and exit the field from the same field side. Hence, after the robots have completed the sequence of "Start", "Direction-1", "Direction-2" and "Direction-3", the remaining columns in the field are just 4, so this would imply that at least two robots would exit to a different field side. If that is not allowed, as in the case here considered, the robots adapt the team size to allow all of them the exit from the field top part. As such, robots R2 and R3 just leave the field, while R1 continues the cover, thus verifying the constraint (Fig. 9(a)). It is also worthwhile to note that an alternative solution would have been just to drop R3 and let R1 and R2 complete the coverage, still verifying the constraint.

*Case II (Maximum and Minimum Size of the Team):* In the example of Fig. 9(b), we consider a field with $r = 6$ and

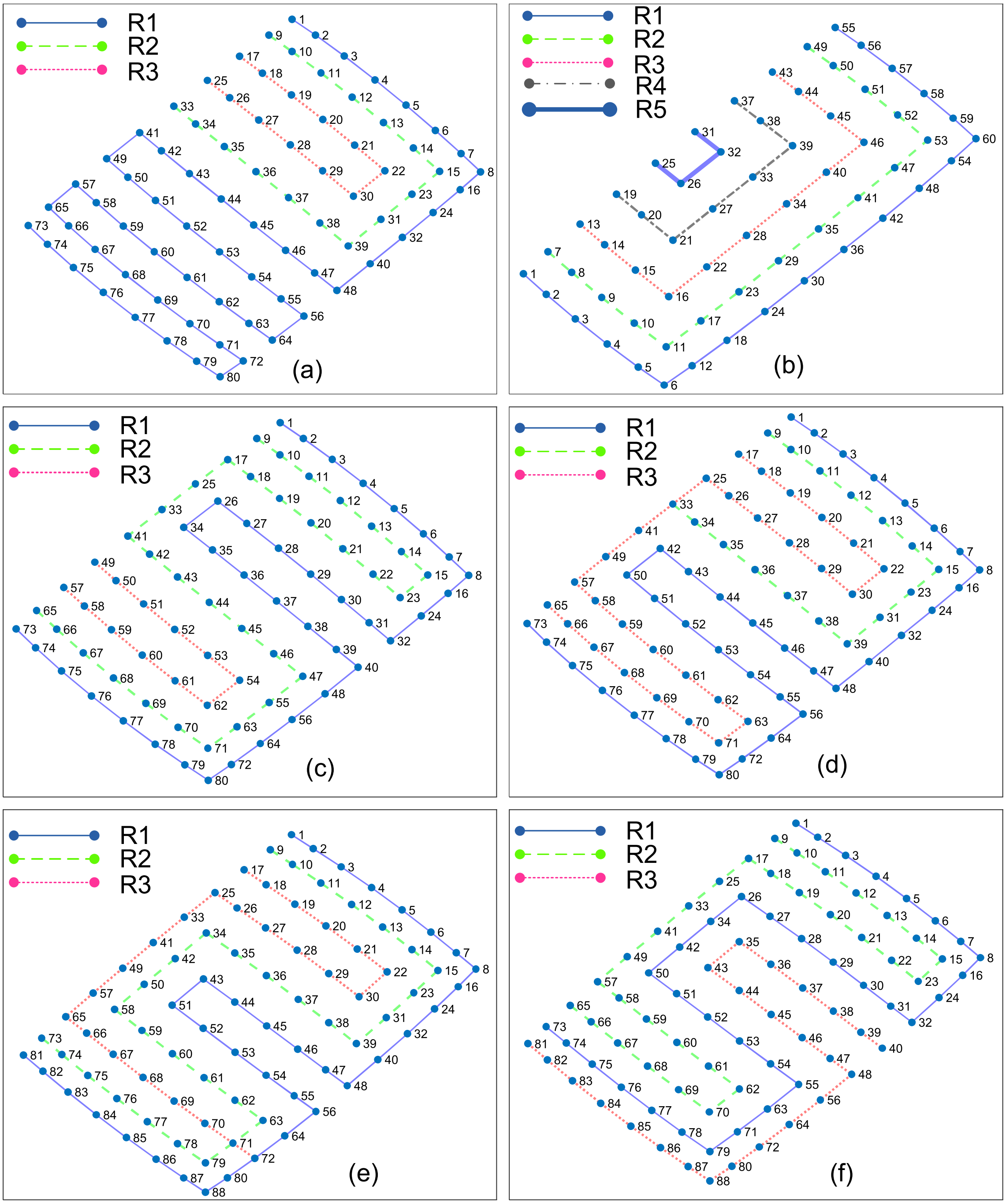


**FIGURE 9.** Simulation results of different scenarios, with a variable number of robots joining and leaving the team on the fly.

$c = 10$, and discuss the maximum and the minimum number of robots to maintain the team on the field from the beginning to the end of the coverage. As discussed previously, the number of columns covered by a team with $n$ robots in a single NOMRT cycle is $2n$. As stated previously, $n < r$ to have robots working efficiently in the field. Hence, to preserve the properties of the NOMRT, the maximum number of robots in the team should be

$$n = min\left(\frac{c}{2}, r - 1\right) \tag{4}$$

Hence, for the case considered, using Eq.(4), the maximum number of agents is $n = 5$, as depicted in Fig. 9(b).

*Case III (Joining and Leaving the Group):* In the example of Fig. 9(c) and Fig. 9(d), we consider a field with $r = 8$, $c = 10$, and a variable number $n$ of robots. In particular, in the example of Fig. 9(c), the coverage starts with $n = 2$ robots, while a third robot joint at node 49. Instead, in the example of Fig. 9(d), the coverage starts with $n = 3$ robots and then shrinks to $n = 2$ when robot R2 leaves at node 33. Notice that in both cases, all the robots respect the side constraint,

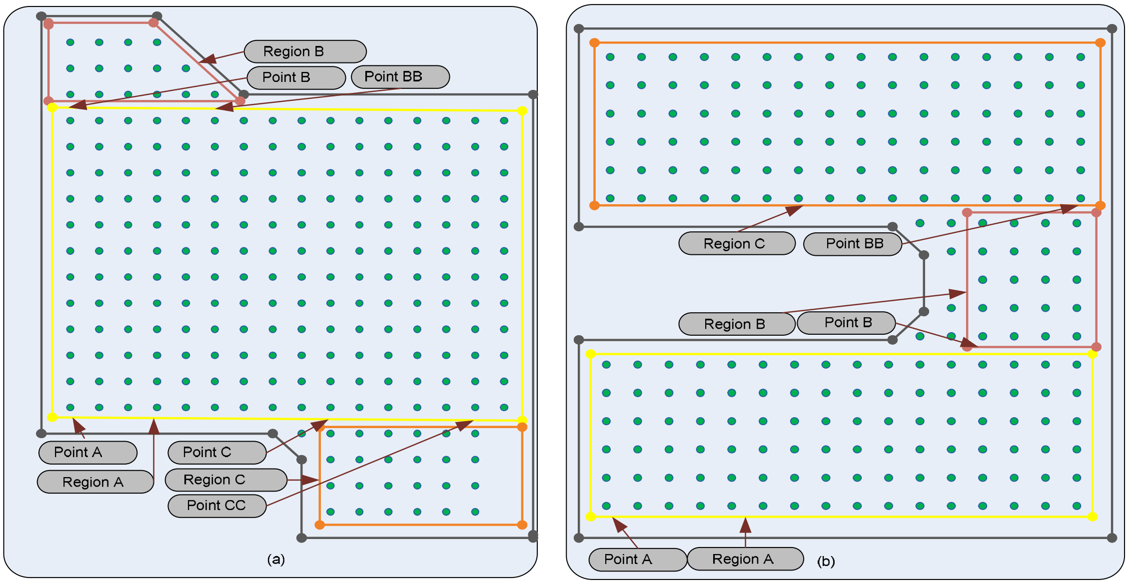


**FIGURE 10.** Decomposition of the complex field to simple sub-region.

i.e., they enter and exit the field from the same field side.

The examples of Fig. 9(e) and Fig. 9(f) consider the adaptation of the number of robots dictated by the number of rows and columns of the field, minimizing the overall robot paths. Such adaptation to the number of robots can be executed online or instantiated at the beginning of the planning phase.

When the real field does not satisfy the assumptions reported in Section III, it can still be subdivided into sub-regions. For instance, in Fig.10, both diagrams (a) and (b) are representations of a sample of a complex map/field, with plants represented in green dots under the SRI method. The division of the field is to insert the larger sub-regions that satisfy the rectangular assumption and remove the odd part of the field not satisfying it: This is an idea that has been applied several times in the literature, e.g., quad-tree decomposition to map a generic region in space [69], [70]. With reference to Fig. 10(a), Region-A follows the assumption and can be covered using a multi-robot approach following the proposed CPP algorithm. The odd regions are Region B and Region C.

Single-robot approaches can be used to cover Region B, with the robot entering, e.g., through Point B and exiting through Point BB after covering it. The team of robots covering Region A with the proposed CPP, may start covering Region A from Point A and, due to its capability of changing the team on the fly, can share one robot at Point B to cover Region B from its current team size. Similarly, the robot can join back to the team covering Region A at Point BB after the coverage of Region B. The Region C of Fig. 10(a), since it satisfies the assumptions, can be covered using the proposed CPP, with its entry and exit points as Point C and Point CC, respectively. The feature of entering into or exiting from the team at all possible sides of the field aids in the reduction of off-task movements of the robot, which is one remarkable feature to be noted in the proposed CPP algorithm that concurs with the optimality for the path as defined in this paper. In the case of Fig. 10(b), all the 3 created sub-regions, are following the assumptions and can be approached using the proposed CPP algorithm. The covering order of all the sub-regions is Region A, then B, and finally C. Notice that the spare plants out of all the regions, can be covered by single robots using straightforward existing solutions. The authors would like to point out that, again, this is possible in all cases using part of the robots of the team at any time, which is a remarkable feature of the proposed multi-robot CPP solution.

As a consequence of the previous discussion, the mentioned decomposition method is used to create the ROI as per the assumptions, even when complex shape fields like the ones inFig.10 are considered. The authors would like to point out that the odd regions of Fig. 10(a) can be in principle further decomposed into rectangular areas: in the limit, there can exist a rectangular area covering just a single plant.

However, since the rectangular shape is a prerequisite of the multi-robot proposed CPP, which enables the dynamic features of the algorithm, it is actually pointless to verify such conditions for fields with a very reduced number of rows and columns, since a multi-robot approach would be an overkill.

Hence, as for the cases of Fig.10, a desired minimum number of plants in the field can be set as desired and it's a design parameter for the CPP algorithm

It is worth mentioning the work in [71] on task planning framework which can effectively coordinate multiple robots. It is handled in a few layers, starting with extracting a task sequence satisfying the collaborative task specification, decomposing it, and allocating it to robots. Each robot

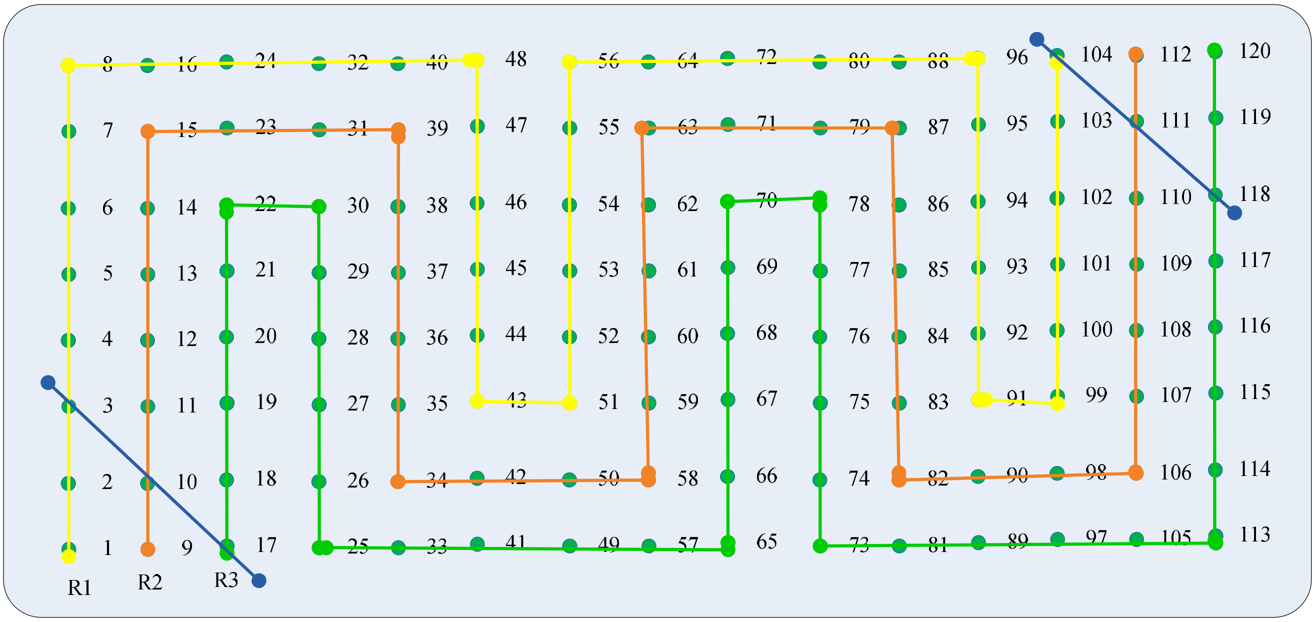


**FIGURE 11.** The NOMRT algorithm on the field with 8 rows and 15 columns.

synthesizes its execution strategies to minimize the wait time for collaboration.

It is worth proving the equal depletion of batteries for all the robots. Considering Fig.5, the end of the "Start" part and the start of the cycle part is denoted by a line connecting nodes 3, 7, and 11. This synchronization line and the next are denoted by diagonal lines, the second connecting the nodes 33, 37, and 41. Between these two synchronous points, the robots R1, R2, and R3 cover the distances of 10 edges (equivalent to 10 $d_f$). The same can be proved using the simulation output Fig.7d, where the distance between the two synchronization lines is 16 $d_f$. To understand the time taken to complete the coverage of a field, we have considered a field of 8 rows and 15 columns, reported in Fig. 11. The distance traveled by all the robots between the two denoted synchronization lines (blue segments in Fig. 11) is 37 $d_f$. Including the "Start" and the "End" parts, all robots take an overall of 39 $d_f$. The "Start" process takes time equal to 2 $d_f$, which is equal to the "End" part, and both represent just a small fraction of the entire covered path.

## V. CONCLUSION

An optimized coverage path planning algorithm to cover a field using a multi-robot team is proposed. The multi-robot coverage algorithm proposed is a natural evolution of the basic single-robot coverage algorithm based on the trapezoidal method or zig-zag movements. Three possible extensions to multi-robot are proposed, i.e., MRT, PCMRT, and NOMRT, which are all based on the most efficient trapezoidal approach. The cost of the coverage is compared using the total distance taken by the robots for all three solutions. In this manuscript, the authors disclosed how the trapezoidal method can be extended to CPP for multi-robot, still preserving its simplicity and effectiveness, and leading to the NOMRT solution.

In addition to being the most effective among the investigated solutions,

- The NOMRT provided consistent coverage of ROI despite the difference in robot team size, a distinctive feature stemming from its capability of online adjustment to changing operational scenarios.
- The change in team size can happen on any side of the field, thus reducing the amount of off-task movements of the robots.
- Another relevant feature of NOMRT is the generation of equal-length path sections, which ensures an even depletion of robot batteries.

The authors analyzed different operating and time-varying scenarios, which are typical for agricultural applications, and showed that the simplicity of the path design is yet effective and robust against robot failures or robot team size changes: The authors do believe that this is a clear advancement with respect to the state of the art.

- Furthermore, due to the limited amount of information to be exchanged among the robots in the team, the algorithm can be easily extended to a distributed solution, which will be part of future implementation.

At the moment of the paper writing, the algorithm has not yet been implemented on an actual platform, therefore future developments will focus on the implementation of the algorithm on actual hardware in an actual field. Another drawback is imposed by the requirement and the assumptions reported in Section III. Indeed, different requirements may impose constraints limiting the exposed performance.

Moreover, the assumptions on the regularity of the field, the necessity to execute the weeding along the path, and the constraints on the robot dimensions may not be satisfied, thus imposing additional research to adapt the algorithm to different fields and robots (with possibly different dynamics) as well as to deal with adaptive solutions when the field characteristics change online due to unforeseen conditions (e.g., some of the routes are temporarily blocked by some of the robots or natural obstructions).

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