Bio-Inspired Complete Coverage Path Planner for Precision Agriculture in Dynamic Environments

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***Abstract*—This paper proposes a bio-inspired Complete Coverage Path Planner suitable for several precision agriculture tasks, such as terrain and crop mapping, inspection, and crop spraying. This grid-based method reproduces the dynamics of the neural activity in a biological neural system to represent dynamically varying environments. By providing appropriate inputs to the neurons of the grid, their neural activity can be exploited to guide the robot towards uncovered regions of the area and enforce the desired coverage pattern. Both known and unexpected obstacles can be easily handled, since the sudden discovery of an obstacle simply modifies the local neural activity online. Thus, the need for complete re-planning phases is canceled. A deadlock-escaping mechanism is also proposed to efficiently recover from dead ends. Finally, simulation results are provided to show the flexibility and effectiveness of the method in dynamic environments.**

***Index Terms*—Complete Coverage Path Planning, Bio-Inspired, Intelligent Agriculture Machine, Precision Agriculture**

I. Introduction

In the latest years, the increase in population and the expansion of urban areas has led the agricultural sector to look for innovative solutions to increase the productivity of farmlands. In this context, precision agriculture [1] aims at enhancing the efficiency and reducing the cost of agricultural processes relying on intelligent agricultural machines, in the form of both Unmanned Ground Vehicles (UGVs) and Unmanned Aerial Vehicles (UAVs) [2], [3]. The introduction of automation technologies in the agricultural sector has risen robotics problems heavily related to field logistics, such as the Agricultural Routing Planning (ARP) problem, [4]. In particular, many ARP problems consist of efficiently achieving a complete traversal of an entire work region and, hence, can be classified as Complete Coverage Path Planning (CCPP) problems. Terrain and crop mapping, inspection, and crop spraying are typical precision agriculture examples of such tasks, [1].

The CCPP problem is studied in different fields and applications, both in indoor and outdoor environments [5]–[7], and is addressed by employing both offline and online planners. Offline CCPP methods, while being able to achieve optimal coverage planning results, require the entire knowledge of the work region and are usually characterized by higher computational times [8]. Common examples for offline coverage planners are the exact cellular decomposition methods, which divide the original map into smaller regions that can be traversed with simple patterns, e.g. sweep movements. These methods are commonly adopted for agricultural purposes. As an example [9] and [10] focus on optimizing the visiting sequence of the sub-regions as well as their ingress and egress point. Even though these method can achieve optimal coverage, they lack reactivity and are not suitable to face contingencies, as any change in the environment would trigger an entire re-planning phase. Such a re-planning could introduce waiting times that may compromise the execution of the task, especially for unmanned systems with limited time autonomy.

On the other hand, online coverage planning methods are more reactive and suitable for dynamic and unknown environments. They usually rely on a grid-based discretization of the work region, which allows handling of the robot's maneuvering capability [8], [11], [12]. As an example, in [13] genetic algorithms are adopted to optimize the coverage in a local grid surrounding the robot's current position. In [14], the coverage is achieved by iteratively selecting the node of the grid that minimizes the translational and rotational distances w.r.t. the current position while remaining in the proximity of previously visited nodes. The local approach of these methods reduces the computational effort. A promising method is proposed in [15]–[17], where the dynamics of a biological neural system are exploited to model dynamically varying environments. Nodes characterized by higher neural activity represent uncovered regions, while obstacles are identified by negative neural activity. Even though the results prove the adaptability to dynamic scenarios, the solution obtained is highly sub-optimal. Furthermore, online planners can suffer from deadlock situations in which the robot is surrounded by obstacles or already covered areas, and require escape strategies.

In this work, an online Bio-Inspired Complete Coverage Path Planner (BI-CCPP) is proposed to address coverage problems in precision agriculture. The method is derived from [15]–[17]. By appropriately shaping the external input and the objective function, this work enhances its performances and adapts the coverage strategy to different applications. Furthermore, a novel escaping mechanism is proposed for deadlock situations, which still occur in state-of-the-art implementation. The following sections are organized as follows. Sec. II exposes the problem statement and the contribution of the proposed method w.r.t. the state of the art. In Sec. III the mathematical model of the BI-CCPP is detailed. Simulation results are presented and discussed in Sec. IV, including a comparison with the state-of-the-art counterpart of the proposed method. Our conclusions are drawn in Sec. V.

II. Problem Statement and Contribution

This work focuses on the Complete Coverage Path Planning problem for precision agriculture coverage operations. Given the 2D map of the work region, the CCPP computes the path that allows the robotic machine to traverse the entire area, avoiding the obstacles located in it. However, to maximize the safety of such automated operations, the CCPP should be able to quickly react to the presence of unforeseen obstacles. Furthermore, due to the variety of coverage tasks associated with the agricultural sector, e.g. mapping, inspection, spraying, and harvesting, the CCPP should be characterized by a high level of flexibility in its formulation. Such flexibility allows the end-user to slightly modify the behavior of the CCPP and adapt it to the application of interests, e.g. favoring coverage based on concentric patterns or sweep movements.

The Bio-Inspired Complete Coverage Path Planner (BI-CCPP) proposed in this work takes into account these considerations. The main advantages of this method w.r.t. the literature are: *(i)* its grid-based nature cancels the need to decompose the work region into smaller units, a practice that is usually encountered in agricultural coverage planners, [9], [10]; *(ii)* its computational efficiency allows to easily consider sudden variations in the work region and unforeseen obstacles, overcoming the offline nature of many field coverage planners, [9], [10], and enhancing the safety of automated precision agriculture; *(iii)* the proposed formulation of the external input acting on the work region and of the objective function used to select the next location increases the performances and the flexibility w.r.t. its literature counterparts, [15]–[17], making the BI-CCPP versatile and suitable for a wide range of coverage tasks; *(iv)* the deadlock-escape mechanism proposed allows to efficiently escape from deadlocks and move towards uncovered areas of the work region.

III. Bio-Inspired Complete Coverage Path Planner

A. Bio-inspired topological model

The main concept of the proposed method is to develop a neural system, whose dynamic neural activity represents the dynamically varying environment. Such a neural network is obtained by discretizing the work region in a grid composed of squared cells with side l, in which each node represents a neuron. The dynamics of each neuron is characterized by the shunting equation [18], described as:

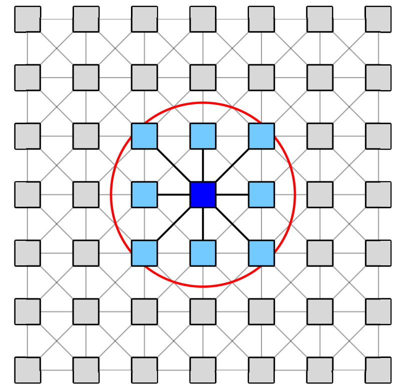

Fig. 1. Representation of neural connections between the central neuron (blue) and the neighboring neurons (light blue) within its receptive field (red).

$$\frac{dx_i}{dt} = -Ax_i + (B - x_i)\left([I_i]^+ + \sum_{j=1}^{K} \omega_{ij}\,[x_j]^+\right) - (D + x_i)\,[I_i]^- , \tag{1}$$

where A, B, D are positive constants representing the passive decay rate, the upper and the lower bounds of the neural activity, x_i is the neural activity of the $i-th$ neuron, bounded in $[-D, B]$ and the functions $[a]^+$ and $[a]^-$ are defined respectively as $\max(a, 0)$ and $\max(-a, 0)$. The terms $\left([I_i]^+ + \sum_{j=1}^{K} \omega_{ij}\,[x_j]^+\right)$ and $[I_i]^-$ represent the excitatory and inibitory inputs acting on the $i-th$ neuron. In particular, $\sum_{j=1}^{K} \omega_{ij}\,[x_j]^+$ expresses the excitatory input caused by the positively excited neurons among the K neighboring ones within the $i-th$ neuron's receptive field of radius r_0. The connection weight between the $i-th$ neuron and its $j-th$ neighbor is $\omega_{ij} = \frac{\mu}{d_{ij}}$, where μ is a positive constant and d_{ij} is the euclidean distance between neurons. In most of cases, $r_0 = 1.5l$ and $K = 8$, as shown in Fig. 1. Finally, I_i represents the external input to the $i-th$ neuron and is determined by the environment of the work region, in order to reflect any change in the scenario. In the current literature [15]–[17], it is defined depending on the status of the $i-th$ node as:

$$I_i = \begin{cases} E_u & \text{if it is not covered yet} \\ -E_o & \text{if it is occupied by an obstacle ,} \\ -E_c & \text{if it is alreday covered} \end{cases} \tag{2}$$

where $E_u = E_o = E \gg B$, E is a very large positive constant and $E_c = 0$. In such a way, the activity of uncovered areas remains at high positive values, while regions occupied by obstacles possess strongly negative neural activity and already covered cells are characterized by intermediate positive values due to the activity propagation through neural connections. The shunting equation of Eq. (1) guarantees that only positive values of activity are propagated among the neurons, hence uncovered areas globally attract the robot, while obstacles block the propagation only locally. Since the external input of uncovered areas E_u is equal in each area of the work region, however, it is difficult to effectively control the pattern characterizing the coverage.

B. External input shaping

This work proposes to exploit the external input of uncovered areas E_u to enforce desired behaviors on the BI-CCPP. Supposing that a gradual coverage based on sweep movements along the Y direction and driving direction towards $+X$ is desired, $E_u(X)$ should decrease as X increases. A formulation suitable for this purpose is:

$$E_u(X) = E\left(2\left(\frac{X_M - X}{X_M - X_m}\right)^2 + 0.5\right), \tag{3}$$

with X_m, X_M being respectively the minimum and the maximum value of X in the work region. In this way, the neural activity of uncovered regions is higher for lower values of X and viceversa, inducing the robot to gradually move from lower to higher values of the X coordinate.

Differently, when concentric movements are preferred, $E_u(X,Y)$ should be shaped as a paraboloid centered in the center of the work region. Thus:

$$E_u(X,Y) = E\left(2\frac{(X - X_c)^2 + (Y - Y_c)^2}{(X_M - X_c)^2 + (Y_M - Y_c)^2} + 0.5\right), \tag{4}$$

where $X_c = \frac{1}{2}(X_M + X_m), Y_c = \frac{1}{2}(Y_M + Y_m)$ are the coordinates of the work region's centre and X_M, X_m, Y_M, X_m represent the maximum and minimum values of the coordinates X and Y. In such way, the neural activity of nodes close to the border is higher than the one of central nodes, and a general inward movement is enforced.

C. Traversing strategy

To efficiently achieve complete coverage of the work region, the robot should travel a short path, make fewer turns and avoid visiting already covered areas multiple times. Unlike the state-of-the-art implementation [15]–[17], the proposed BI-CCPP generates the coverage path considering not only the neural activity landscape of the map and the previous location of the robot, but also the state of the neighboring areas. Considering a given current robot location p_c in the grid-map discretizing the work region, the next robot location p_n is selected by

$$p_n \Leftarrow \max\left(x_j + cy_j + dz_j, j = 1, 2, \dots, K\right), \tag{5}$$

where x_j is the neural activity of the $j-th$ neighbor of p_c and c, d are positive constants. Variable y_j is a function penalizing sharp turns and is computed as:

$$y_j = 1 - \frac{\Delta\theta_j}{\pi}, \tag{6}$$

with $\Delta\theta_j \in [0, \pi]$ being the absolute heading angle change between the current and the next robot moving directions, i.e. $\Delta\theta_j = |\theta_j - \theta_c| = |\mathrm{atan2}(y_{p_j} - y_{p_c}, x_{p_j} - x_{p_c}) - \mathrm{atan2}(y_{p_c} - y_{p_p}, x_{p_c} - x_{p_p})|$, and p_p being the previous robot location. Finally, variable z_j is computed as:

$$z_j = \frac{K_{j_c} + K_{j_o}}{K_j}, \tag{7}$$

where K_{j_c}, K_{j_o} represent respectively the number of already covered and occupied neurons among the K_j neighbors of the $j-th$ neighboring neuron of p_c. This term favors the selection of the next locations that remain close to already covered areas and obstacles, inducing the robot to proceed gradually in the coverage task. In this way, uncovered areas are less likely to be left behind during the coverage and, consequently, the need to traverse already visited areas is reduced.

Once the next location p_n has been identified, the robot moves from p_c to p_n, whose status is set as covered. The external input of the network $I(X,Y)$ is updated to reflect eventual changes in the environment, the neurons' dynamics for the current step are computed using Eq. (1) and the neural activity of the whole map $x(X,Y)$ is updated with discrete time step dt. Then, the whole process is repeated iteratively until complete coverage of the work region is achieved.

Algorithm 1: Deadlock-escape pseudoalgorithm

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Input: neural activity x(X,Y), current position p_c,
       nominal parameters c_nom, d_nom, μ_nom
Output: neural activity x(X,Y), next location p_n
while x_j ≤ x_i ∀ j ∈ [1,K] do
    if x_i ≥ 0 then
        Update x(X,Y) using Eq. (1);
    else
        Increase μ;
        Update x(X,Y) using Eq. (1);
    end
end
Select next location p_n using Eq. (5) with c = d = 0;
Reset c, d, μ to initial c_nom, d_nom, μ_nom;
```

D. Deadlock-escaping strategy

Due to the local nature of the BI-CCPP, the algorithm may encounter deadlocks, i.e. situations in which the robot is surrounded by areas that are already covered or occupied by an obstacle. In such cases, the neural activity of the neighborhood is lower than or equal to the one characterizing the current position. To successfully escape from such deadlocks, this work proposes to modify Eq. (2) by imposing the external input for covered regions to be slightly negative, i.e. $0 < E_c \ll E$. The selection of this parameter is fundamental for the escape mechanism expressed in Alg. 1.

Suppose that the robot encounters a deadlock when located at p_c, which identifies the $i-th$ neuron ($x_j <= x_i \ \forall\ j \in [1,K]$). At first, the neural activity of the network is iteratively updated until $x_i < 0$. Then, the parameter governing the intensity of neural connections μ is gradually increased as the activity landscape continues to evolve. As a result, the activity level in the map gradually propagates only from the areas of the map that are not covered yet and, thus, possess high activity values. Once the activity propagation reaches the proximity of the $i-th$ neuron and at least one of its neighbors assumes $x_j > x_i$, the robot selects the neighboring neuron with maximum activity as the next location p_n, i.e. using Eq. (5) with $c = 0, d = 0$. Afterward, the value of the parameter c, d, and μ are reset to their nominal values, resulting in the neural activity gradually contracting towards the uncovered regions and in the robot following its trail.

Note that, if the parameter E_c is not chosen as previously described at the beginning of Sec. III-D, the neural activity of already covered regions would assume close to zero but positive values. This, coupled with the increase of μ, would result in neural activity propagating also from visited regions of the map, potentially causing the robot to be stuck in an already covered area without being able to complete the coverage. Thus, the aforementioned modification of Eq. (2) is essential to successfully execute the deadlock-escaping mechanism.

IV. Results

In this section, the results obtained using the proposed BI-CCPP to completely cover a dynamic and partially unknown work region are analyzed. The operating area is a region $200\ m \times 200\ m$ large, which is discretized using square cells of $l = 10\ m$. The area contains two known obstacles and one unknown obstacle that forces a deadlock upon its discovery. The starting point (S) of the robot is placed at $p_0 = [0, 0]^T\ m$. The tests are carried out using Matlab and the proposed algorithm is exploited to perform the two patterns mostly used for coverage purposes: sweep and concentric movements. A comparison with the literature counterpart of the BI-CCPP is provided, too. Finally, computational times considerations are carried out.

A. Coverage based on sweep movements

The parameters of the BI-CCPP in Eq. (1) are selected as $A = 20, B = D = 1, E = 50, E_c = 0.5, dt = 0.01\ s$. In order to induce a $+X$ driving direction with sweep movements along the Y axis, the external input $I(X, Y)$ is set using Eq. (2) and (3). The nominal value of μ is set to $\mu_{nom} = l$ and, when the deadlock escape mechanism is triggered, its value is gradually increased at each time step following the law $\mu^{t+1} = \mu^t + 0.1\mu_{nom}$. Selecting μ as a multiple of the cell side l is a convenient choice since it ensures that the connection weight ω_{ij} does not depend on the size of the cells. In this way, the same coverage behavior can be reproduced despite scaling the scenario. Finally, the nominal values of the parameters of Eq. (5) are selected through a tuning process as $c_{nom} = 0.05$, $d_{nom} = 0.1$.

The results are depicted in Fig. 2, in which: *(i)* black and white cells represent, respectively, occupied and free areas, *(ii)* yellow and red patches identify known and initially unknown obstacles, *(iii)* dashed red lines represent path segments overlapping with already covered cells. Initially, the robot traverses the work region with regular sweep movements until a deadlock occurs in (A). However, thanks to the proposed escaping mechanism, the BI-CCPP is able to recover efficiently from this situation and continue the coverage task (B). From this point on, the sweep pattern is deformed by the shape of the obstacles. Nonetheless, the $+X$ driving direction of the coverage strategy still remains noticeable. When the robot reaches the point (C) and the $L-$shaped obstacle is discovered, intentionally creating another deadlock (D). The escaping method is used to return to the coverage task in (E). The deadlock escaping mechanism is activated again in (F) and (H), successively guiding the robot towards the top-right corner of the map and achieve complete coverage of the map (T).

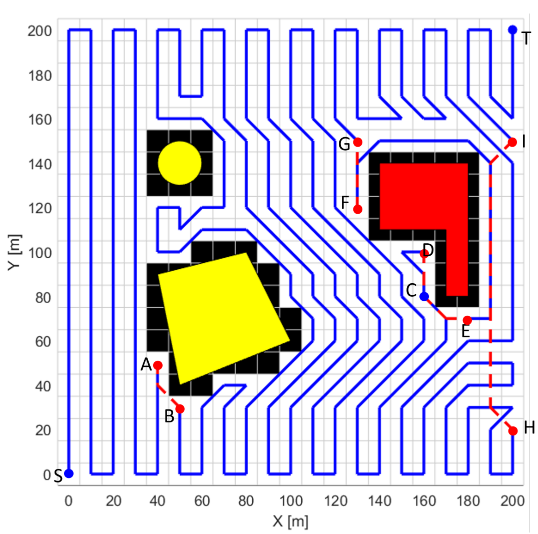

Fig. 2. Sweep-based coverage path with sudden discovery of the unknown obstacle (red) in (C).

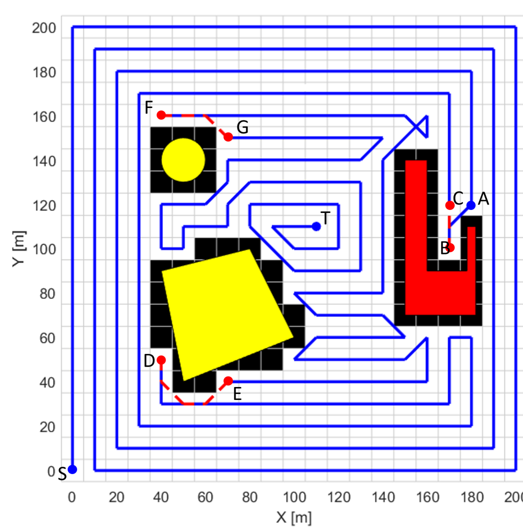

Fig. 3. Concentric coverage path with sudden discovery of the unknown obstacle (red) in (A).

B. Coverage based on concentric movements

The parameters of the BI-CCPP are selected analogously to the case of sweep movements, with the following exceptions: *(i)* the external input $I(X, Y)$ is set using Eq. (2) and (4) to induce a concentric pattern during the coverage task; *(ii)* the nominal value of the parameter d_{nom} of Eq. (5) is lowered to $d_{nom} = 0.05$ to help in following concentric movements rather than turning back to stay close to visited regions.

The results are depicted in Fig. 3, in which objects and paths are color-coded as in the previous case. The robot starts covering the work region with concentric movements, until the unknown $U-$shaped obstacles is discovered (A). Note that the form of such obstacle has been selected to artificially induce a deadlock, (B). As in the previous case, the BI-CCPP is able to effectively return to the coverage task exploiting the proposed escape strategy. Analogous considerations can be repeated for the the next deadlock points, (D) and (F). Finally, due to the induced concentric pattern, the robot achieves complete coverage of the working region in the central area of the map (T).

C. Comparison with the literature counterpart

The proposed method is now compared to its literature counterpart, [15]–[17]. The parameters of the method are selected as follows: *(i)* the external input $I(X, Y)$ is set using exclusively Eq. (2), which means $E_u = \text{const} = E, E_c = 0$; *(ii)* the evaluation of the variable z_j is removed from Eq. (5) setting $d_{nom} = 0$; *(iii)* the proposed deadlock escape mechanism is replaced by the bio-inspired path planning from a starting point to a target point adopted in the literature, [15], [19], [20].

Graphical results are depicted in Fig. 4, while quantitative comparison is reported in Tab. I. Initially, the coverage follows the behavior of the concentric case due to the absence of z_j in the objective function, Eq. (5). The algorithm is still capable of reacting to the sudden discovery of the $U-$shaped obstacle in (A), and the path planning method from [19], [20] is still able to escape the deadlock point (B). However, the concentric pattern is lost and substituted by local and smaller patterns as the robot encounters other obstacles. This phenomenon leads to several deadlock points, (D), (F), (H), (J), (L), (N), and to a final point (T) which is neither in the center nor on the border of the work region. This behavior is caused by the selection of $E_u = \text{const}$, which does not induce any kind of priority to the uncovered cells of the map. Accordingly, the number of steps, deadlocks and repetitions characterizing the literature counterpart of the BI-CCPP is higher w.r.t. both the sweep-based and concentric movements cases. The proposed method outperforms the literature counterpart even considering the percentage of repetitions over planning steps, with a result of $4.65\%, 1.59\%, 5.36\%$ respectively for the sweep, concentric and literature counterparts cases. Finally, as for the length of the planned path, the concentric movements based BI-CCPP achieves the lowest value, improving the performances of the literature counterpart even considering the similarity in their initial coverage behavior. On the other hand, the higher length

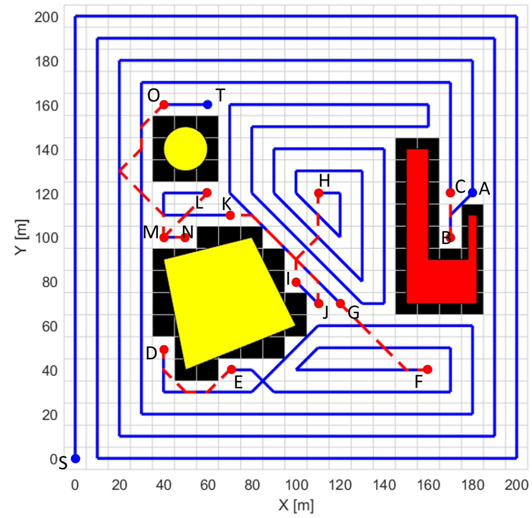

Fig. 4. Coverage path obtained through literature counterpart with sudden discovery of the unknown obstacle (red) in (A).

TABLE I
PERFORMANCES COMPARISON

	Sweep	**Concentric**	**Literature**
N_{steps}	387	377	392
Length$[m]$	4197.2	3840.4	4077.4
$N_{deadlock}$	4	3	7
$N_{repetitions}$	18	6	21

of the sweep-based BI-CCPP is caused by the sweep strategy itself, which forces the robot to remain closer to already visited areas and consequently move diagonally.

Such results demonstrate that the proposed reformulation of the neurons' external input and of the objective function is capable of inducing desired patterns on the BI-CCPP, increasing its performances and flexibility w.r.t. to its literature counterpart.

D. Computational times and applicability considerations

The BI-CCPP has been tested on a computer with Intel Core i7-8750H (2.20 GHz) and 16 GB RAM. More than 375 planning steps are executed in each simulation and the mean computational time for a single planning step is $4.8 \times 10^{-4}\ s$. Even when deadlocks occur, the maximum computational time required to plan a single step remains limited to $2.6 \times 10^{-2}\ s$. Hence, the BI-CCPP can easily face unforeseen obstacles or changes in the working scenario, even if they require the re-computation of the last planning step.

Eventually, considering the extension of typical work regions for precision agriculture tasks, the BI-CCPP can also use the current knowledge of the environment to compute an estimate of the remaining coverage path in a small amount of time. Considering the worst case of the results shown, i.e. when the robot is still at the starting point, the method requires just $1.3 \times 10^{-1}\ s$ to compute an estimate of the remaining coverage path. This capability can be conveniently used to check the feasibility of the task, taking into account the endurance of the robotic agricultural machine.

V. Conclusions

This work proposes an online and computationally efficient Bio-Inspired Complete Coverage Path Planner for precision agriculture tasks. The grid-based algorithm takes inspiration from the dynamics of neural activity in biological neural systems to discretize the work region into a neural system and model the dynamicity of the environment. Its enhanced flexibility allows the user to easily vary the coverage strategy by shaping the external input of the neurons and adjusting the value of the objective function's parameters. Such a feature makes the method suitable for several applications, e.g. terrain and crop mapping, inspection, and crop spraying. The novel escaping mechanism to recover from deadlock situations exploits the capability of neurons to transfer the neural activity across the work region and correctly attract the robotic agent towards uncovered areas.

The results demonstrate the ability of the BI-CCPP to outperform its literature counterpart and induce the desired behaviors and patterns for the coverage task. Furthermore, the algorithm is able to successfully avoid all the obstacles present in the work region, even initially unknown ones. Finally, all intentionally induced deadlocks are efficiently overcome and the method's capability to achieve complete coverage is corroborated.

Future works will focus on the correlation between the field of view of the robot's sensors and the dimensions of the cells. Finally, path local optimization methods will be included to further improve the performance of the algorithm.

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