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Path Planning Algorithm for a Robot

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Abstract. This paper provides a comprehensive paper of the Complete Coverage Path Planning (CCPP) algorithm for autonomous mobile robots, with a particular focus on applications in robotic vacuum cleaners, also known as robovacs. The CCPP aims to create a path for a robot to fully cover an objective region while minimising overlap and neglect, thereby ensuring efficient use of time and energy. As the use of autonomous robots in household and industrial environments grows, the demand for practical coverage algorithms becomes increasingly critical. The paper research existing CCPP methods, including the 'Combined' algorithm, the Boustrophedon Cellular Decomposition algorithm, and the genetic algorithm. The advantages, limitations, and applicability of each method are analysed, and the challenges, including real-time adaptability, computational efficiency, and robustness in unknown environments, are highlighted. Finally, the paper discusses the future directions of CCPP research, including multi-robot coordination, adaptive coverage strategies, and the integration of machine learning techniques to enhance performance. This paper aims to provide insights for both researchers and practitioners looking to develop more efficient and adaptive CCPP solutions for real-world applications.

Keywords: Complete coverage path planning (CCPP), coverage rate, computational load

1. Introduction

With the rapid advancement of science and technology, autonomous vacuum cleaning robots are becoming increasingly common in homes. These robovacs help reduce manual work by cleaning spaces on their own. The global household robot market, which includes vacuum and mopping robots, already makes up about 81% of the market share [1]. However, a significant challenge for these robots is to cover the entire floor with high efficiency and low energy use.

The way to solve this problem is the Complete Coverage Path Planning (CCPP) algorithm. This algorithm ensures a robovac can clean the entire floor without re-entering the same area or omitting any spots. A good CCPP algorithm can reduce cleaning time, save energy, and improve cleaning quality. Many methods have been developed to solve this problem. Some use random collision patterns, and some use advanced ideas like SLAM or AI, such as the Ant Colony Algorithm (ACA) [2]. The random walk method uses simple sensors like infrared. It is easy and strong in unknown areas, but the coverage is usually very low. So, more planned methods are now being used instead. One example is the boustrophedon decomposition planning algorithm, which provides significantly better coverage but requires strong localisation.

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There are many kinds of CCPP algorithms, and their use depends on factors such as the complexity of the space, the availability of maps, the quality of the sensors, and the type of hardware used. In practice, a method that works well in a simple, fixed home may not work in a messy, changing warehouse, and the other way around. Additionally, trade-offs, such as coverage rate versus computing cost, make it challenging to determine the best method for all cases. Because of this, many studies look at just one algorithm in one type of setting, so there is still no complete picture [3,4].

To fill this gap, this paper gives a structured paper of the CCPP algorithm for robovacs. It examines both the theory and its real-world applications. Map needs, coverage level, and hardware needs can be grouped into these algorithms. For each group, the paper discusses the key working ideas and their performance in example cases, drawing support from past studies. This step-by-step comparison provides a framework for evaluating the strengths, limitations, and optimal applications of various CCPP methods.

By consolidating dispersed knowledge into an accessible and logically structured reference, the target is to assist researchers, engineers, and industry practitioners in making informed design choices for next-generation autonomous cleaning systems. Ultimately, I hope this work will not only clarify the current state of CCPP research but also inspire new developments that push the boundaries of efficiency, adaptability, and robustness in autonomous floor-cleaning technology.

2. Background of CCPP

The complete coverage path planning (CCPP) refers to the process of generating a path that allows a mobile robot to cover an entire space without missing any part and with minimal overlap and neglect. Therefore, coverage path planning (CPP) not only requires a high coverage rate but also needs to optimise indicators such as coverage time, path length, and the number of turns [5]. This capability is especially critical in-service robots such as robotic vacuum cleaners (robovac), agricultural field robots, and warehouse inspection systems. In household environments, an efficient CCPP algorithm is crucial for saving time, reducing energy and increasing coverage rate.

Within the literature, several core concepts are commonly used to evaluate and compare CCPP methods. The first is coverage rate, defined as the ratio between the area covered by the robovac and the total area of the target environment. A high coverage rate is generally the primary goal of any CCPP algorithm. The second is the overlap rate, which refers to the proportion of the area that is covered more than once. In contrast, a small degree of overlap can be tolerated for thoroughness; excessive overlap often leads to inefficiency and wasted energy. Another important distinction is between offline and online CCPP methods. Offline approaches rely on static environmental information and assume that a complete map of the workspace is available in advance, allowing the entire path to be planned before execution. In contrast, online methods are more adaptable, as they can operate in dynamic environments by generating or modifying the coverage path in real-time. These definitions form the conceptual foundation for understanding the subsequent paper and analysis of the CCPP algorithm in this paper.

3. Algorithm categories

3.1. 'Combined' algorithm

The 'combined' algorithm is integrated by four different algorithms, which are random walk, spiral, 'S' shape pathway and wall follow [6]. This algorithm is designed to create a more efficient and cost-

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effective robovac. In this case, this robovac only requires two more bumper sensors and three cliff sensors. To be specific, the bumper sensor is used for sensing obstacles rather than a traditional IR proximity sensor, because the bumper sensor can receive signals from a wide range and even detect sharp barriers [7]. Therefore, it can clearly indicate to Robovac whether the obstacles in front are present by communicating a signal, either '0' or '1'. This is because the bumper sensors are placed 2cm above the ground, so they can only detect barriers that are at least 2cm high. In addition, three cliff sensors are designed on the underside of the unit and are used to prevent a drop-off. The infrared sensors emit 38kHz of infrared light to detect the height difference, and the results are obtained in the form of a signal of '0' and '1'.

3.1.1. Iirandom walk

This algorithm is one of the fundamental approaches without the implementation of the exact realisation of the route project [8]. The robot moves forward until it detects an obstacle, and then turns a random degree to continue its movement. To prevent the situation of corner escape angle, in which the robot is trapped in corners, the lateral front bumper sensors are used to sense bumping into an obstacle, thereby assisting in determining the turning angle [9].

3.1.2. Spiral algorithm

This algorithm is particularly suitable for simple and empty, yet non-rectangular spaces, allowing the robot to create a larger circle. The core of this algorithm is for the robot vacuum to gradually expand outward along a spiral path, starting from the centre points or a specific starting point, and cover the entire space. The spiral algorithm terminates when the robot reaches the set target boundary or detects the barriers.

3.1.3. 'S' shaped pathway

This algorithm is a strategy commonly used in overlay CCPP, especially in environments with regular structures and no complex obstacles. The basic idea is to cover all target spaces in sequence along a zigzag or S-phased path within the region. In this case, the robot starts from a specific starting point and moves forward. As it reaches the boundary of the space, the robot moves parallel to the left or right. It will continue to move along another S-shaped path. This process will be terminated once the robot has traversed the entire field. In this design, the robotvac can guarantee that each position is traversed without omission, covering the target areas in the shortest time [10].

3.2. Wall follower

This algorithm enables a robot to navigate along a specific static obstacle (e.g., walls) or boundary, ensuring that the robot always remains on one side of the obstacle. This algorithm is highly suitable for situations where robots must navigate around obstacles in the environment, especially when the global map is unknown. The lateral bumper sensors are used to sense the obstacles. By constantly adjusting the robot’s movement, it is kept at a certain distance from the wall to avoid collisions. If encountering corners or more complex barriers, the robot will make steering adjustments and continue to travel along the new fence. Finally, if the wall no longer exists or returns to the starting points, the algorithm will stop. This method is very suitable for sketching out the target region.

In the 'combined' algorithm, the above four different algorithms are executed sequentially until the entire surface area is thoroughly cleaned.

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3.2.1. Boustrophedon Cellular Decomposition (BCD)

The Boustrophedon Cellular Decomposition (BCD) algorithm is one of the most widely used approaches for CCPP [11]. The term 'boustrophedon' literally means 'the way of the ox', referring to the classical farming practice where an ox ploughs the field by walking in a straight line across its entire length, turning at the boundary, and then proceeding back in the opposite direction in a parallel track. By repeating the motion, the ox systematically and efficiently covers the entire field, a principle that inspires the zig-zag patterns commonly used in robotic coverage tasks. In the context of CCPP, the BCD extends this principle by decomposing a complex and cluttered environment into a set of simpler subregions known as cells. The decomposition is achieved through critical point analysis, which detects changes in the connectivity of free space as a virtual sweep line passes through the environment. Each resulting cell is topologically simple and well-suited for back-and-forth coverage, allowing the robovac to systematically traverse the entire area with minimal overlap or omission [12].

BCD looks simple in concept, but to work well, it needs special hardware and software. The algorithm depends on accurate spatial decomposition, so it needs reliable geometric information about the space. Because of this, BCD is seen as an offline method. To enable decomposition and navigation, the robovac requires sensors that can accurately detect barriers and boundaries. Standard options are laser range finders (LiDAR) and infrared sensors. These can capture the shape of the environment [13]. Also, marker detectors or visual sensors can be used to recognise landmarks. These help with localisation during coverage. But in practice, BCD has also been modified to work in online cases by combining it with SLAM, also known as concurrent mapping and localisation (CML). SLAM enables robots to build a map of an unknown space step by step, while also locating themselves. This mix allows for BCD to operate in partially known or changing areas, but it increases the computing demand. Large or messy environments require robust computing power to facilitate cell decomposition, map updates, and safe path planning [14].

The BCD process has three stages: environmental decomposition, coverage inside each cell, and movement between cells. First, the environment is modelled as a 2D free space, where obstacles and boundaries are clearly marked. Then, a virtual sweep line is moved across the space. When the line encounters a change, such as entering or leaving a barrier, a critical point is identified. These points cut the space into a set of non-overlapping cells. Each cell is smaller and easier to cover than the whole space. Second, the robovac covers each cell with a zig-zag path, similar to the boustrophedon ploughing motion. This ensures the robot covers the entire cell without missing any parts or overlapping excessively. Third, when one cell is fully covered, the robot finds a path to move to the next cell. These moves are planned to reduce travel costs while ensuring the robot covers the entire space.

3.2.2. Genetic Algorithm (GA)

The genetic algorithm (GA) is a population-based metaheuristic optimisation method inspired by the process of natural selection and biological evolution [15]. In the context of robotic coverage, the GA is used to optimise the sequence and structure of the robot's path so that the entire environment can be covered with high efficiency and minimal redundancy. Unlike deterministic methods, such as BCD mentioned above, which generate structured coverage patterns, the GA concentrates on finding (near-)optimal solutions to path planning problems that are often computationally intractable. This makes the GA particularly useful in highly complicated environments where exact approaches are infeasible.

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The primary motivation for applying the GA in robovac lies in its capability to optimise multiple performance criteria simultaneously. For instance, a typical CCPP task requires not only maximising coverage rate but also minimising path length and the time cost. The GA achieves this by encoding possible robot trajectories as 'chromosomes' and then iteratively improving these candidate solutions through genetic operations such as selection, crossover, and mutation. Over successive generations, the population coverage towards paths that yield high coverage with reduced cost metrics [16]. Compared to traditional heuristic approaches, such as random walk, the GA demonstrates better adaptability in cluttered household environments where efficiency is crucial.

The hardware requirements for the GA-based coverage path planning largely depend on the specific implementation. Since the GA itself is a high-level algorithm, it does not impose constraints on sensors or actuators. However, for a robovac to execute GA-generated paths, it must possess accurate localisation and mapping capabilities to ensure that the planned route corresponds to the actual environment. Typically, this involves integrating odometry sensors, inertial measurement units (IMUs), LiDAR or infrared sensors for obstacle detection, and possibly cameras for visual localisation. In addition, because the GA requires iterative computation and optimisation, onboard processing units must have sufficient computational resources, or the algorithm may be offloaded to external processors.

The implementation process of the GA in CCPP can be described as follows. First, the environment is discretised into a grid or graph representation, where each cell corresponds to a potential robot position. Next, an initial population of possible coverage paths is randomly generated. Each path is encoded as a chromosome, often represented as a sequence of grid cells or movement commands. A fitness function is then defined to evaluate path quality, typically combining metrics such as coverage rate, overlap rate and energy consumption. Through iterative cycles of selection (choosing better paths), crossover (combining paths), and mutation (introducing variation), the population evolves towards paths with higher fitness. Finally, the best solution is selected as the robovac's execution path [17].

For classification, the GA is usually seen as an offline algorithm because it needs a complete map of the space to test possible solutions and find the best path. However, new studies have explored online GA methods, where optimisation is performed step by step as the robot explores new areas [17]. These methods mix the flexibility of GA with sensor-based navigation. This way, the robovac can react to changes in the space while still using the optimisation power of evolutionary computation.

4. Comparison and analysis

The CCPP algorithm for robotic vacuum cleaners encompasses a range of strategies. These go from simple sensor-based methods to structured decomposition techniques and evolutionary optimisation methods. The Combined Algorithm, Boustrophedon Cellular Decomposition (BCD), and Genetic Algorithm (GA) are three main types. Each has different trade-offs in how hard it is to set up, what hardware it needs, how efficient it is, and where it can be used.

The Combined Algorithm uses four simple methods — random walk, spiral, S-shaped path, and wall follows and runs them one after another. It is simple because it mainly uses direct reactions to basic sensor input. This makes it easy to use, but it lacks a systematic approach. In contrast, BCD uses critical point analysis to cut the space into smaller parts. Each part is then covered with a zig-zag path. This method is very systematic and gives full coverage with little overlap. The GA works differently. It uses an optimisation process based on biological evolution. Here, many candidate paths are tested and improved step by step to raise coverage efficiency and lower path cost. Unlike

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BCD, GA does not provide a perfect solution, but it can yield near-optimal paths in complex, unstructured spaces.

In terms of hardware, the combined algorithm is the least demanding. It requires only bumper sensors for obstacle detection and cliff sensors for drop-off avoidance, making it a cost-effective and suitable option for low-budget, consumer-grade robovacs. The BCD, however, demands precise environmental perception to perform spatial decomposition, requiring advanced sensors such as LiDAR and infrared sensors, as well as SLAM capabilities when applied in unknown environments. The GA does not inherently depend on specific sensors. Still, practical execution requires robust localisation and mapping modules (e.g. IMU, vision-based system) to ensure that the optimised trajectory corresponds to the actual workspace. Moreover, due to iterative computation, GA implementations require greater onboard or external computational resources compared to the other two methods.

The combined algorithm offers flexibility and robustness in simple environments, but its reliance on basic reactive behaviours often results in redundant coverage and longer completion times. The BCD achieves significantly higher efficiency by ensuring structured and systematic coverage of each decomposed cell. Its deterministic nature reduces redundancy and guarantees full coverage, though performance may degrade in a dynamic environment where environmental changes necessitate repeated decomposition. The GA is highly adaptable, capable of optimising multiple objectives such as coverage rate and path length simultaneously. However, due to its stochastic nature, GA may require substantial computation time to converge and does not always guarantee globally optimal coverage.

As shown in Table 1, the combined algorithm is best suited for small-scale, relatively uncluttered household spaces where low hardware cost and robustness outweigh the demand for efficiency. BCD is highly effective in structured environments, including large household areas, where accurate mapping data is available. GA demonstrates strength in cluttered spaces, as well as in scenarios requiring multi-objective optimisation. In addition, hybrid approaches that combine GA with decomposition methods or sensor-based strategies have shown promise in bridging the gap between adaptability and coverage.

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Table 1. Comparative analysis of path planning algorithms in terms of principles, requirements, and performance

Criteria	Combined Algorithm	Boustrophedon Cellular Decomposition (BCD)	Genetic Algorithm (GA)
Principle	Integrates four basic strategies: random walk, spiral, S-shaped path, and wall-follower. They are executed sequentially.	Decomposes the environment into a simple 'cell' using critical point analysis. Each cell is covered with zig-zag trajectories.	Population-based optimisation inspired by natural selection. It iteratively refined the candidate coverage path.
Hardware Requirement	Minimal: 2 bumper sensors and three cliff sensors.	Requires precise sensing (LiDAR or cameras) and mapping. It is often integrated with the SLAM.	Depends on localisation and mapping (odometry, IMU). It requires higher computational power.
Execution Efficiency	Robust but redundant. Its coverage is less systematic, so a longer cleaning time is required.	High efficiency. It has systematic full coverage with minimal overlap.	Near-optimal path efficiency. It can balance multiple objectives, but may require a long convergence time.
Applicability	Best suited for small-scale home spaces and budget-friendly robovacs.	Suitable for structured, large-scale, or semi-cluttered spaces with available maps.	Effective in complex, cluttered, or irregular environments and flexible optimisation for multiple targets.
Strengths	Simple, cheap, robust, easy to implement	Systematic and predictable. Guarantees full coverage with structured patterns.	Flexible, adaptable, and multi-objective optimisation. It is suitable for irregular layouts.
Weaknesses	Redundant paths and poor efficiency in complex spaces.	Requires accurate mapping. Computationally heavy in the dynamic settings.	Although computationally expensive, the stochastic nature does not guarantee a global optimum.

5. Open issues and future directions

Despite significant progress in CCPP for robotic vacuum cleaners, many problems remain unsolved. These problems limit the efficiency, flexibility, and practical application of the algorithms. One main problem is the balance between coverage efficiency and hardware cost. The Combined Algorithm is cheap because it only uses simple bumper and cliff sensors. But it often repeats work and has lower coverage in complex spaces. On the other hand, BCD gives systematic and almost complete coverage. However, it requires costly and accurate sensors like LiDAR, which also increase computing needs. GA can provide optimised paths, but it requires numerous repeated calculations. This is hard for real-time use on low-cost machines. So, finding a way to keep low hardware needs while still getting high coverage is still an open issue.

Another significant challenge is navigating changing or unknown spaces. BCD is mainly offline. It works well in fixed spaces, but it struggles when obstacles move or when people or furniture change the map. GA is more flexible, but because it depends on repeated optimisation, it is slow to react in real time. The Combined Algorithm can respond fast in unknown areas, but it cannot give the best overall path. These problems show that better CCPP methods are needed. The goal is to adapt to changes in the space while keeping high coverage.

A further issue is combining CCPP with SLAM. BCD needs very accurate maps for decomposition. GA also needs good environment models to optimise paths. The Combined

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Algorithm does not require detailed maps; however, this lack of detail results in reduced global awareness and lower efficiency in structured spaces. New SLAM methods can map and locate simultaneously in unknown spaces. But making SLAM work closely together with CCPP for adaptive, online coverage is still a complex problem.

Looking ahead, future research directions can address these limitations from several perspectives. To begin with, the hybrid algorithms that combine the systematic decomposition of BCD, the optimisation ability of GA, and the robust reactivity of combined approaches may deliver improved performance across diverse environments. Furthermore, the development of online and adaptive CCPP integrated with incremental SLAM will enable robovacs to optimise their coverage dynamically as they encounter new areas, reducing dependency on pre-computed maps. Moreover, learning-based methods, particularly reinforcement learning, have shown promise in recent years, allowing robots to learn optimal coverage strategies from experience rather than depending on manually designed rules.

In addition, the multi-robot coordination represents a promising direction, as multiple robovacs can collaboratively divide and cover large environments while minimising redundancy. Furthermore, energy-aware robots are expected to gain attention, considering battery efficiency and the demand to adapt robot trajectories in ways that minimise interference with human activities. Finally, advances in hardware-algorithm co-design, such as the integration of lightweight RGB-D cameras or ultra-wideband localisation, will play a crucial role in enabling more intelligent CCPP without imposing excessive computational costs.

6. Conclusion

This study gives a full paper and comparison of CCPP algorithms for robotic vacuum cleaners. It focuses on the Combined Algorithm, BCD, and GA. The paper first looked at the basic ideas of CCPP and then showed how each algorithm tries to reach the main goals: high coverage, low redundancy, low energy use, and adaptability to different spaces. The paper showed that BCD is a classic and systematic method. It provides reliable and comprehensive coverage, but it requires accurate maps and advanced sensors. GA brings an optimisation-based method. It works well in complex or cluttered spaces by finding near-optimal solutions under many factors. However, it requires a significant amount of computation, which can slow down real-time use. The Combined Algorithm is different. It uses simple methods like random walk, spiral, S-shaped path, and wall following in sequence. This makes it cheap and easy to use with basic hardware. But in more structured spaces, its coverage is less efficient [17].

By comparing these algorithms, it becomes evident that each approach embodies a trade-off between efficiency, robustness, adaptability, and cost. No single method is universally superior, and the choice of algorithm depends heavily on the operating environment, available hardware, and user priorities. This analysis further underscores that real-world challenges, such as dynamic environments, scalability, energy efficiency, and user interaction, remain open issues that existing methods cannot fully address.

Looking ahead, the evolution of CCPP is expected to be driven by hybrid and adaptive frameworks that combine the structured reliability of decomposition methods, the optimisation power of evolutionary computation, and the reactivity of sensor-based navigation. At the same time, the integration of learning-based approaches, particularly reinforcement learning and deep neural networks, offers promising opportunities for enabling robovacs to adapt to household environments in real-time through experience. Other future directions include multi-robot collaboration, human-

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aware navigation, and energy-aware path planning, which will further enhance the practicality and intelligence of robotic cleaning systems.

In conclusion, while existing algorithms such as the Combined method, BCD, and GA have significantly advanced the field of robotic coverage path planning, the next generation of solutions must strive toward adaptive, intelligent, and resource-efficient strategies. Bridging the gap between theoretical robustness and practical deployment will be crucial to developing autonomous household robots that deliver efficient, reliable, and user-friendly performance in increasingly diverse and dynamic real-world settings.

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