

# Toward Mass Customization of a Robot's Morphology Design for Improving Area Coverage

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**Abstract**—Floor cleaning robots have been developed to cater to building maintenance needs. Complete area coverage is crucial for a floor cleaning robot, and its morphology design plays a vital role in realizing complete area coverage. However, floor cleaning robots with fixed morphologies have difficulty in achieving a high area coverage performance. Mass customization of a robot's morphology would improve its productivity in terms of area coverage. This paper proposes a novel system that can be used for mass customizing the morphology of a robot to improve area coverage performance in an environment of interest. The customized morphology is determined through an optimization technique by considering an environment of interest and design constraints. The area coverage of a candidate morphology design is evaluated by simulating the robot navigation in an environment of interest. Generalized pattern search, particle swarm optimization, and surrogate optimization are independently considered optimization techniques. Experiments have been conducted considering the cases of robot deployments. The statistical conclusions on experimental results validate that the proposed system can synthesize a morphology that significantly improves the area coverage performance in an environment of interest.

## I. INTRODUCTION

Buildings with complex structural shapes have been constructed to enhance the living quality and experience [1]. Cleaning is one of the routine maintenance tasks demanded by these buildings to preserve the living standard and aesthetic appearance. Robots have been developed to resolve the complication associated with the human labor-based cleaning of buildings [2]–[4]. Floor cleaning is a primary focus of robot-aided cleaning of buildings since floors have to be cleaned more often [5]. Thus, developments of dirt detection methods [6]–[8], advanced sensing and perception mechanisms [9]–[11], efficient path planning algorithms [12]–[14], and human-robot interaction [15] have been studied to improve the adoption of robots for floor cleaning. Complete area coverage is one of the foremost aspects expected from a mobile robot intended for applications such as floor cleaning [16], [17].

Much attention has been paid to developing path planning algorithms that ascertain the complete area coverage of mobile robots [18], [19]. In this regard, the work [20] proposed a coverage method based on cellular decomposition. Path

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planning algorithms based on evolutionary algorithms such as genetic algorithm and ant colony optimization have been studied to achieve complete area coverage while improving efficiency [21], [22]. Path planning methods based on bio-inspired neural networks have also been proposed for efficient coverage [23], [24]. These bio-inspired neural networks are also capable of coordinating multiple robots for coverage.

Although many navigation algorithms have been developed to realize efficient complete area coverage, as discussed above, area coverage performance could often be degraded in typical indoor environments [25], [26]. Moreover, a robot faces accessibility issues in environments where objects with complex shapes, such as furniture, are scattered. The cited work proposed concepts to improve the coverage performance of floor cleaning robots by rearranging the environment instead of enhancing the functions of the robot. Nevertheless, such environment alterations for the sole purpose of improving a floor cleaning robot's performance may not be convenient on all occasions. Reconfigurable robots have also been introduced for floor cleaning to improve the area coverage performance [27], [28]. These reconfigurable robots can improve the area coverage since the morphology reconfiguration allows them to access narrow spaces that would not be accessible by a robot with a fixed morphology. However, the system complexity of a reconfigurable robot is much higher compared to a robot with a fixed morphology [29]. For example, a reconfigurable robot needs mechanical structures, additional actuators, and internal sensors to facilitate the reconfiguration. The inclusion of additional electro-mechanical components increases the complexity in terms of hardware design. Deployment and maintenance costs would rise with the system complexity of a robot. The increased system complexity is the major downside of the deployment of reconfigurable robots for floor cleaning.

Square, circular, and D-shape are the mostly seen morphologies of commercially available floor cleaning robots. However, these fixed morphology designs are planned for the general case. As a result of the consideration of generalized design, complete area coverage could not be realized in most of the environments [25], [26]. In contrast, the use of a morphology design tailored to a specific environment (with some constraints) would improve the area coverage in the environment compared to a non-tailored design. Therefore, applying a mass customization strategy for floor cleaning robots' morphology designs would be beneficial in improving performance. However, a strategy for mass customization of a robot's morphology design for improving area coverage performance has not been proposed yet.

This paper proposes a novel system that can be used for mass customization of the morphology design of a robot to ascertain the complete area coverage in an environment of interest. The system has been developed in such a way that the design constraints can be fed into it to facilitate mass customization. The main contributions of this paper are the conceptual development of a mass customization strategy for the problem of complete area coverage of robots and the design and development of a system to synthesize the morphology design that improves the coverage. An overview of the proposed system is given in Section II. The system proposed for synthesizing the customized morphology design for an environment of interest is presented in Section III. Experimental results are analyzed and discussed in Section IV. Concluding remarks are given in Section V.

## II. SYSTEM OVERVIEW

### A. Rationale behind the Proposed System

The rationale behind the proposed system is explained with the aid of the scenario depicted in Fig. 1, where three robots with different morphologies cover an environment cluttered with objects. Here it is assumed that the footprint areas of the robots are the same. The consideration of the equivalent footprint areas for robots avoids prejudice due to the size factor (Obviously, the coverage of a smaller robot is higher than that of a larger robot due to high accessibility. However, coverage time increases when the robot gets smaller.). In addition, a mass customization process prefers equivalent sizes for customized designs to facilitate the design constraints, such as the placement of motors and batteries.

The possible area coverage of the environment when deploying a robot with a square-shaped morphology is explained in Fig. 1(a). Due to space constraints, the robot could not access the narrow spaces, and much area is left uncovered in this event. Fig. 1(b) depicts the probable coverage of the same environment by a robot with a rectangular-shaped morphology. In this example scenario, the coverage of the rectangular-shaped robot is comparatively higher than the square-shaped robot. However, a considerable amount of space is still left without covering. The coverage of a robot with a pentagon-shaped morphology is considered in Fig. 1(c). In this event, a substantial improvement in coverage

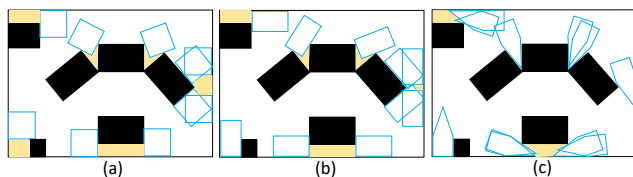


Fig. 1. Variation of area coverage with robots with different morphologies. The areas in solid black represent the obstacles in the environment. Shapes created by blue lines represent the shape of the robot in each case. The shaded areas represent the areas that the robots would not cover. The robots are placed here in such a way that it highlights the inaccessibility. (a): A case of a square-shaped robot. (b): Coverage from a rectangular-shaped robot. (c): A case of a pentagon-shaped robot.

could be observed compared to the previous two events. Moreover, these three explanation cases demonstrate that the area coverage would be substantially varied with the shape of the robot even though the size is the same. Therefore, using a robot with a morphology optimized for the environment would realize the complete area coverage to a greater extent. Nevertheless, the design constraints imposed by the actuators and modules should also be considered in this regard. Thus, developing a mass customization strategy for the morphology of a robot that maximizes the coverage in an environment of interest is challenging.

### B. Functional overview

A functional overview of the proposed system for determining the customized morphology of a robot corresponding to a given environment is depicted in Fig. 2. The metric map corresponding to the environment of interest should be fed into the system. This map can be created either manually or using a mapping robot equipped with a lidar sensor. The robot morphology is constrained by factors such as the dimension of the actuators and sensors, as well as their proper placements. Hence, design constraints such as minimum and maximum lengths and widths, form factor, and the number of vertices of the robot should also be fed to the system. The morphology synthesizer module determines the optimum shape with the aid of the two submodules; the optimizer module and the performance evaluator module. An optimization algorithm is run on the optimizer module in this regard. The performance evaluator module evaluates the coverage performance of each candidate morphology in the given environment. In this regard, the performance evaluator module internally simulates the coverage of a candidate robot design in the environment concerned. The coverage performance determined by the performance evaluator module is used as the fitness of the optimization algorithm. The optimization algorithm determines the optimum morphology that maximizes the fitness. Moreover, a morphology that maximizes the area coverage corresponding to the environment of interest is determined as an output. Apart from that, the coverage performance and a visualization of the coverage map are indicated as outputs.

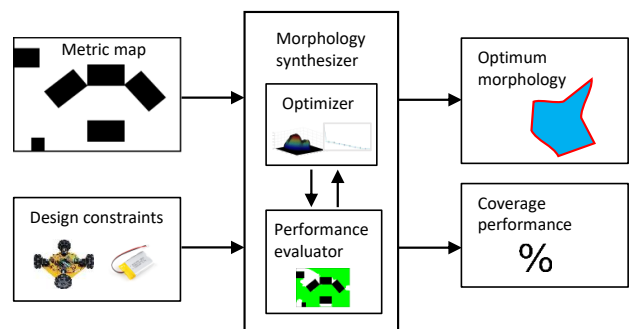


Fig. 2. System overview

### III. SYNTHESIZING THE MASS CUSTOMIZED MORPHOLOGY

The principle of determination of the customized morphology that improves the coverage for an environment concerned is explained with the aid of Fig. 3. The design of a robot's morphology with  $n$  number of vertices on the design space is depicted here. The closed shape created by connecting the successive vertices is the robot's morphology. It is assumed that a straight line connects a pair of successive vertices. Hence, the morphology of the robot is dependent on the positioning of vertices on the coordinate frame.  $x_i$  and  $y_i$  denote the X-axis and Y-axis coordinates of the  $i^{\text{th}}$  vertex. As explained in Section II-A, the coverage performance of a robot in a specific environment depends on the morphology of the robot. Moreover, the positioning of the vertices could alter the coverage performance of robot design.

It is considered that positions of  $m$  number of vertices ( $m \in (0, n]$ ) could be altered to find the optimum shape for an environment of interest, and the remaining  $n - m$  number of vertices are fixed (if all the vertices are alterable, then  $m = n$ ). The number of vertices ( $n$ ) and the number of adaptable vertices ( $m$ ) are user-definable design constraints fed to the system. In the case of  $m < n$ , the positions of fixed vertices should also be given as design constraints by the user. It is assumed that  $n$  and  $m$  are fixed per design process. The area coverage of the robot in an environment concerned would be varied with the variation of these  $m$  vertices. Two parameters are required for defining the position of a vertex. Hence, if  $m$  number of vertices are adaptable, then  $2m$  number of variables that maximize the area coverage should be found in the design process. Furthermore, many combinations of values for these adaptable variables exist. Therefore, evaluation of coverage of all the morphologies resulting from such a large number of combinations to find the optimum morphology is challenging.

Soft computing optimization techniques have proven their effectiveness in coping with similar sorts of optimization problems [30], [31]. The area covered in an environment of interest is the parameter that needs to be maximized. Apart from that, the design constraints should be accounted for during the optimization. The lower and upper bounds of each vertex and the bounded area of the morphology ( $R_A$ ) are considered the constraints for the optimization. The objective function for optimization is defined as in (1), where  $A_C$  is

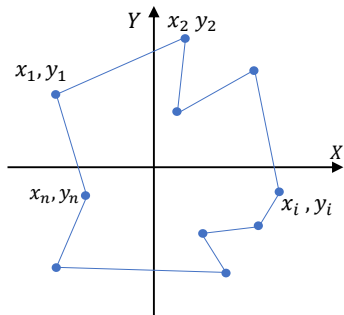


Fig. 3. A robot's morphology on the design space.

the area coverage corresponding to the resulting morphology. Here  $(R_A)_L$  and  $(R_A)_U$  are the lower and upper bound of the robot size defined as a constraint. The percentage area coverage,  $A_C$  is formulated as in (2) yielding to  $A_C \in [0\%, 100\%]$ . The area coverage of the robot in an environment of interest is evaluated by simulating the coverage. Here, the coverage planner used for simulating the coverage should be capable of dealing with different morphologies with the same level of performance. The boustrophedon-motion-based coverage path planner proposed in [32] for a reconfigurable robot is considered here since the morphology reconfiguration is analogous to coping with robots with various morphologies. In the coverage evaluation, it is assumed that the morphology footprint is equal to the active coverage area, considering a floor mopping robot. During the coverage evaluation, the planner only attempts to evaluate the maximum coverage without optimizing coverage based on other performance factors, such as time and energy. Furthermore, the geometric robot shape is solely considered for coverage without considering real driving behavior, leading to possible minor deviations from real-world scenarios. The search space is bounded to  $x_i \in [(x_i)_L, (x_i)_U]$  and  $y_i \in [(y_i)_L, (y_i)_U]$  for the  $i^{\text{th}}$  vertex if  $i^{\text{th}}$  vertex is adaptable. It should be noted that the goal of the optimization is to minimize the cost function, (1), which reflects the contrary performance. Here,  $\{x_i, y_i\}$  represents the set of adaptable vertices.

$$f(\{x_i, y_i\}) = \begin{cases} -A_C(\{x_i, y_i\}), & \text{if } (R_A)_L \leq R_A(\{x_i, y_i\}) \leq (R_A)_U \\ 100, & \text{otherwise} \end{cases} \quad (1)$$

$$A_C(\{x_i, y_i\}) = \frac{\text{Area coverage of the robot } \{x_i, y_i\}}{\text{Space available to cover}} \times 100\% \quad (2)$$

Developments of many optimization techniques for coping with similar kinds of problems could be seen in the literature, and those optimization techniques have advantages and disadvantages based on the nature of the problem [30], [33]. Thus, a set of heterogeneous optimization techniques are considered here. Generalized Pattern Search (GPS) [34], Particle Swarm Optimization (PSO) [35], and Surrogate Optimization (SO) [36] techniques are examined in this regard. GPS is a non-population-based technique that is computationally efficient compared to PSO, a population-based technique that evaluates the cost function many times in an iteration. However, GPS has a higher risk of converging to a local optimum, whereas PSO is more likely to find the global optimum. On the other hand, SO is especially preferred for coping with optimization problems that have expensive (in terms of time consumption and computational power) objective functions. Here, evaluating the objective function of the morphology synthesizer is expensive since simulations have to be carried out to evaluate the area coverage. Thus, SO is considered a contender for the optimizer module of the system. The parameter configuration of the optimization techniques considered in this work is given in Table I.

TABLE I  
CONFIGURATION OF THE OPTIMIZATION METHODS

GPS	PSO	SO
Poll method: GPS Positive basis 2N	Initial swarm span: 2000	Min sample distance: 1e-3
Polling order: Consecutive	Swarm size: $\min(100, 10 \cdot 2m)$	Min surrogate points: $\max(20, 2 \cdot 2m)$
Mesh initial size: 1.0	Inertia range: [0.1, 1.1]	Stopping criteria
Mesh expansion factor: 2.0	Min neighbors fraction: 0.2	Max function evaluation: $\max(200, 50 \cdot 2m)$
Mesh contraction factor: 0.5	Stopping criteria	
Stopping criteria	Max iterations: $200 \cdot (2m)$	
Mesh tolerance: 1e-6	Max stall iterations: 20	
Max iterations: $100 \cdot (2m)$	Function tolerance: 1e-6	
Max function evaluations: $2000 \cdot (2m)$		

#### IV. RESULTS AND DISCUSSION

##### A. Experimental Setup

The complete system has been implemented as a software application. A robot's morphology design with four vertices (i.e.,  $n = 4$ ) was considered to validate the performance of the proposed system. All the vertices were considered adaptive (i.e.,  $m = n$ ). The lower and upper bounds of the vertices were taken as  $x_1 \in [-30 \text{ cm}, 0 \text{ cm}]$ ,  $y_1 \in [0 \text{ cm}, 30 \text{ cm}]$ ,  $x_2 \in [0 \text{ cm}, 30 \text{ cm}]$ ,  $y_2 \in [0 \text{ cm}, 30 \text{ cm}]$ ,  $x_3 \in [0 \text{ cm}, 30 \text{ cm}]$ ,  $y_3 \in [-30 \text{ cm}, 0 \text{ cm}]$ ,  $x_4 \in [-30 \text{ cm}, 0 \text{ cm}]$ , and  $y_4 \in [-30 \text{ cm}, 0 \text{ cm}]$  based on the design constraints imposed by the locomotion system and mopping mechanism. It is considered that the robots were fixed with a differential drive mechanism for locomotion, microfiber mop-pads and a liquid tank for wet cleaning. Furthermore, the lower and upper bounds of the robot's size (i.e.,  $(R_A)_L$  and  $(R_A)_U$ ) were considered 900 and 1000, respectively. This small tolerance of the footprint area avoids prejudice due to size variation instead of shape. When using GPS for the optimization, a square shape was considered the initial solution. The behavior and performance of the proposed system were analyzed in considering the coverage estimations of the proposed system and robot deployments.

##### B. Behavior and Performance of the Morphology Synthesizer

The behavior and performance of the proposed system have been evaluated, considering 15 test environments. Environments that would be highly benefited from using tailored robots, such as hotel rooms, waiting rooms of airports, and meeting rooms, were specially considered for the test environments. The metric maps crafted per the layouts of the environments were fed to the system, and the outputs of the system (i.e., optimum morphology and area coverage) were analyzed. The process was repeated for each optimization technique utilized in this work. Apart from that, a square-shaped robot (a robot with non-tailored morphology) was considered as the baseline for the performance comparison. As sample results, the results obtained for five test environments are given in Fig. 4. The resulting morphology, the coordinates of the vertices, the corresponding area coverage map, and the percentage area coverage (i.e.,  $A_C$ ) for each method are given.

In case 'a', a living room of a single bedroom apartment was considered as the test environment. In the event of

using GPS for the optimization, the vertices of the optimum morphology were determined as (-13.0 cm, 14.9 cm), (15.6 cm, 19.4 cm), (19.0 cm, -11.0 cm), and (-15.0 cm, -11.1 cm). These vertices resulted in a shape that deviated from the standard shape. The percentage area coverage ( $A_C$ ) corresponding to the morphology resulting from GPS was 90.1%. In the events of PSO and SO, two different optimum morphologies were synthesized by the system. The corresponding  $A_C$  was 95.8% and 95.0% for PSO and SO, respectively. In contrast, in the event of the square-shaped robot (i.e., non-tailored), the robot's morphology hinders the accessibility of the space in between the bases of furniture, and a considerable amount of area remains uncovered. Thus, a lower area coverage (79.8%) was observed for the event of the square-shaped robot (i.e., non-tailored) than the area coverages obtained for optimized morphologies.

A robot prototype was developed considering the morphology determined by the PSO (since the estimated coverage was highest for PSO), as shown in Fig. 5. Apart from that, a prototype of a robot with a square-shaped morphology was also considered to compare the performance. Each robot was separately deployed to the environment of case 'a' for the coverage. An overhead camera system was used to track the area coverage of robots within the environment, and the videos were analyzed to create area coverage maps. The areas occluded for the primary camera were separately analyzed. The resulting coverage maps for robot deployment experiments in case 'a' are given in Fig. 5, along with the resulting percentage area coverages ( $A_C$ ). An improved area coverage could also be observed from the event of using the mass customized morphology compared to the event of using a robot with a square-shaped morphology where the percentage area coverages were observed as 92% and 76%, respectively. Slight deviations of area coverages (less than 5%) were observed between simulations and the real robot deployments. These slight deviations are apparent in the nature of the experiment, where the area coverages were formulated based on an analysis of the overhead camera view. Furthermore, similar characteristics could be observed from the coverage maps resulting from the proposed system and the real deployments. Thus, it is justifiable to assume that the coverage maps and the percentage area coverages observed from the real robot deployments comply with the system outputs resulting from the internal simulations. These results confirm the real-world applicability of the proposed

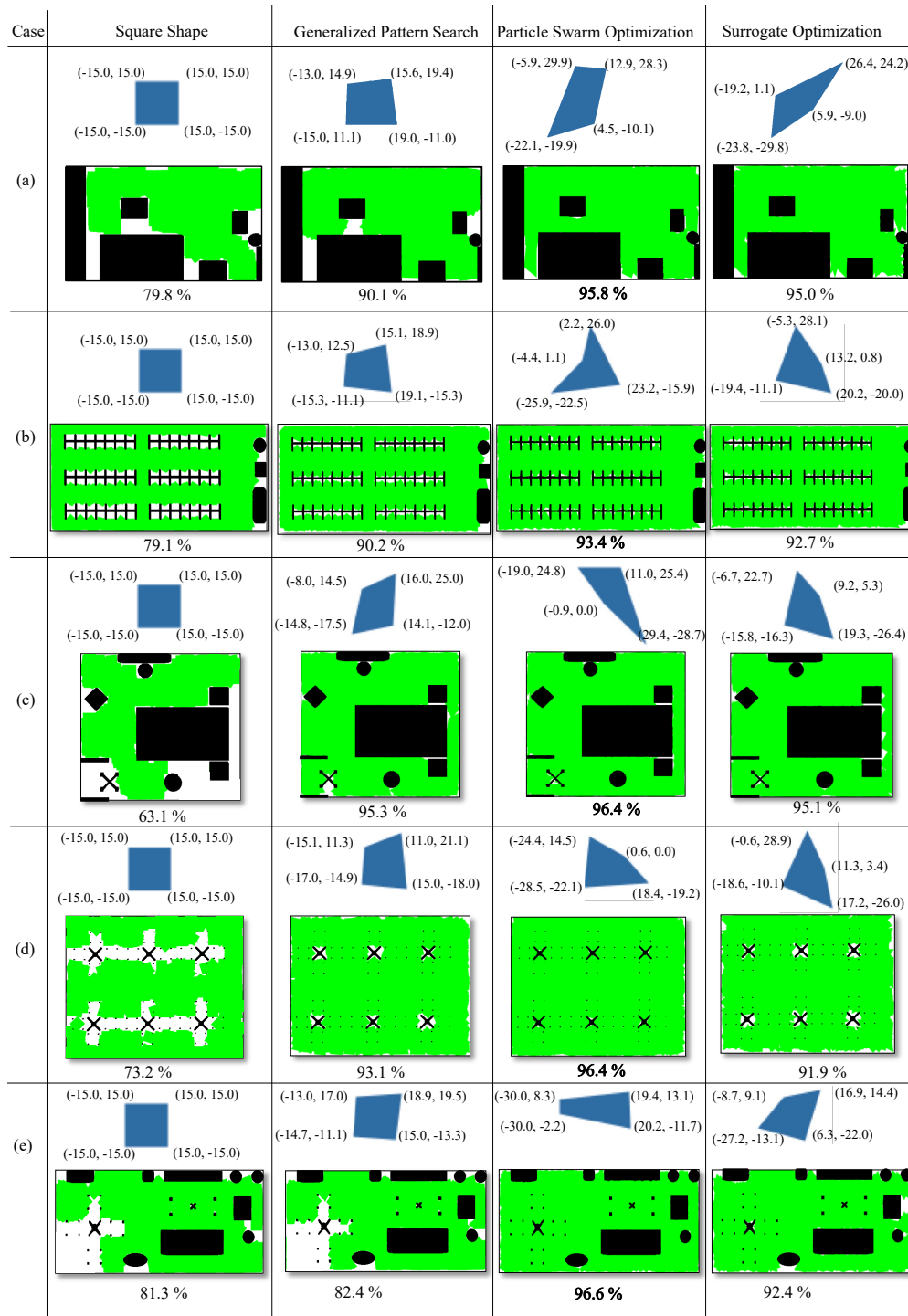


Fig. 4. Sample results of the experiment. The morphologies of the robot are given in blue. In a coverage map, obstacles, covered areas, and uncovered areas are in black, green, and white. It should be noted that the robot morphologies and the corresponding coverage maps are not on the same scale. The coordinates of the vertices are given in cm. The highest recorded value of  $A_C$  of each case is given in bold.

system for synthesizing a mass customized morphology to improve the area coverage performance of a robot in an environment of interest. Furthermore, the results ensure the validity of the coverage performances determined by the proposed system.

Similarly, for all 15 test environments, the lowest  $A_C$  of each test environment was observed from the square-shaped robot. In 12 test environments out of 15, the morphologies

synthesized by PSO recorded the highest coverage, while the morphologies determined by GPS recorded the highest in the other three environments. The means of  $A_C$  obtained from the four events for all the test environments are given in Fig. 6(a) along with error bars. The lowest mean  $A_C$  was observed from the events of non-tailored morphology ( $M = 75.59\%$ ,  $SD = 6.79$ ), while the highest mean  $A_C$  was observed from the event of morphologies synthesized by

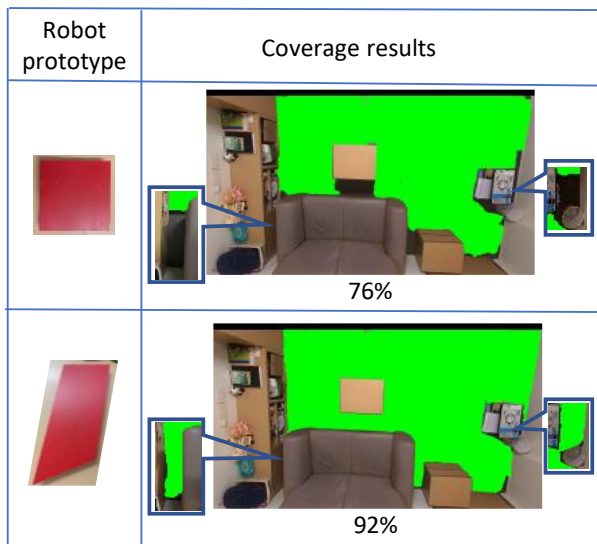


Fig. 5. Comparison of area coverage maps resulted from the deployments of prototypes of robots in the environment of case ‘a’. The deployed prototypes of the robot are also shown.

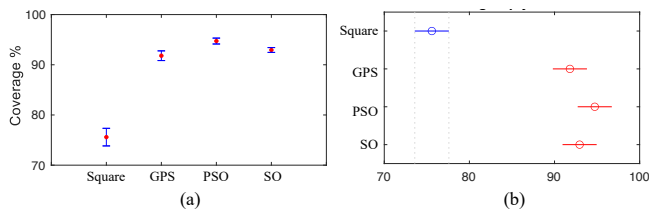


Fig. 6. (a) Variation of mean  $A_C$ . The error bars are drawn to represent the standard error. (b) Interval plots of the multiple comparison test. Here, if intervals of groups overlap, there is no significant difference between the corresponding groups’ means.

PSO ( $M = 94.73\%$ ,  $SD = 2.27$ ). Intermediate area coverage performance were observed from the events of GPS ( $M = 91.81\%$ ,  $SD = 3.74$ ) and SO ( $M = 92.9\%$ ,  $SD = 1.86$ ). A one-way ANOVA test was conducted to assess the statistical significance of area coverage performance among the considered events, revealing a significant difference ( $F_{3,56} = 68.7$ ,  $p < 0.001$ ). Subsequently, Tukey’s honest significant difference criterion was applied for pairwise comparisons. The results are presented in Fig. 6(b), indicating a significantly lower mean  $A_C$  for the square morphology event compared to the optimum morphologies synthesized by the proposed system. However, no significant difference was observed among the mean  $A_C$  values of the events utilizing the three optimization techniques in the proposed system. Therefore, it is concluded that the proposed system significantly improves a robot’s area coverage performance in the environment of interest through morphology synthesis. Additionally, there is no performance deviation in area coverage among the three optimization techniques considered.

### C. Discussion

According to the experimental results of the work proposed in this paper, a lower area coverage performance could be observed from a robot with a non-tailored morphology (on average, the percentage area coverage was observed as 76.7%). This observation can be grounded from the

work [26], which found a similar sort of low area coverage performance from a commercially available floor cleaning robots with non-tailored fixed morphologies in typical environments. Thus, the mass customization strategy proposed in this paper is beneficial for overcoming this limitation during the design of robots for coverage applications such as cleaning.

The proposed system has been developed in such a way that it can be customized based on design constraints and requirements. For example, the number of adaptable vertices, lower and upper bounds of vertices, and bounded area of a morphology design can be configured for synthesizing a tailored morphology for a scenario based on the space requirement for locomotion modules and other electro-mechanical systems. However, it should be noted that the footprint of the robot morphology is assumed to represent the effective coverage. This assumption holds for cleaning robots used for mopping applications. However, for other applications, such as vacuuming, the footprint area may only be partially effective due to the characteristics of the application payload. Therefore, it would be intriguing for future work to explore the design of effective payloads tailored to a robot’s morphology.

The consideration of design constraints based on essential components of a robot facilitates a formulation of a mass customization strategy for the complete area coverage problem of robots intended for area coverage. Therefore, the work proposed in this paper contributed toward developing a strategy for mass customization of a robot’s morphology design for improving area coverage. Mass customization strategies for improving the performance of robots intended for area coverage have not been proposed yet, and the work proposed in this paper can be considered the first work on this novel research niche.

## V. CONCLUSION

A novel system that can synthesize a mass customized morphology design for a cleaning robot that ascertains the maximum area coverage in an environment of interest has been proposed in the paper. A metric map of the environment of interest should be fed to the system and the design constraints that facilitate mass customization. The customized morphology is synthesized through an optimization process considering the area coverage variation of candidate morphologies in the environment of interest. The optimization techniques, Generalized Pattern Search (GPS), Particle Swarm Optimization (PSO), and Surrogate Optimization (SO), are proposed to use in this regard.

According to the experimental results, the area coverage performance of a robot can be significantly improved by using the proposed system to design the robot’s morphology compared to a non-tailored design. Future work expects to consider other performance factors, such as coverage time and energy usage, in conjunction with area coverage for determining optimum morphologies. Additionally, exploration of the morphology designed by the proposed method in environments undergoing dynamic changes is anticipated.

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