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hTetro-Infi: A Reconfigurable Floor Cleaning Robot With Infinite Morphologies

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ABSTRACT The development of floor cleaning robots is an emerging area in robotics. Maximizing the area coverage is a foremost mission for a floor cleaning robot. Reconfigurable floor cleaning robots outperform floor cleaning robots with fixed morphology in the aspect of area coverage. A reconfigurable robot should be more flexible in changing its morphologies by considering the shapes of objects occupied in an environment to gain more coverage. Nevertheless, the state of the art methods of tiling robots considers only a limited number of morphologies for the reconfiguration, which is not sufficient to match the shape of an object. Therefore, this paper proposes a novel method to synthesize an appropriate morphology for a reconfigurable robot in accordance with the shape of an object. The proposed concept is named hTetro-Infi since it is not limited to a finite number of morphologies. The major novelty of the proposed concept overt the state of the art is the consideration of an infinite number of morphologies for the reconfiguration without sticking into a limited number of morphologies. Feedforward Neural Network (FNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) were used for determining the hinge angle required for synthesizing a given morphology. Different configurations of FNNs and ANFISs were trained and evaluated to find the most suitable configurations. The area coverage performance of the proposed hTetro-Infi was compared against that of the state of the art methods of an existing class of tiling robots, which considers only a limited number of morphologies, through simulations. According to the statistical conclusions, the proposed hTetro-Infi is capable of significantly improving area coverage compared to an existing tiling-theory based floor cleaning robot. Furthermore, the area coverage improvement of hTetro-Infi is noteworthy. Therefore, the proposed concept is beneficial in improving the abilities of a reconfigurable cleaning robot. Real-world experiments with the hardware platform of the robot for evaluating the performance is expected to be conducted in the next phase of the work. Furthermore, consideration of hTetro-Infi for navigation through confined areas is proposed for future work.

INDEX TERMS Adaptive neuro-fuzzy inference system, area coverage, feedfoward neural network, tiling robotic, floor cleaning robot, reconfigurable robot.

I. INTRODUCTION

Complex structural buildings with more space are rapidly increasing in the world day by day. Adequate cleaning of those buildings is one of the major concerns. Cleaning is a daily routine process that requires much labor. The labors' efficiency and accuracy may decrease due to the repeating nature of the work. Since the cleaning process is routine, an autonomous cleaning robot can play a vital role in these buildings. Many cleaning robots have been proposed for different cleaning activities such as window cleaning [1], staircase cleaning [2], floor cleaning [3], drainage cleaning [4], pavement cleaning [5] and pool cleaning [6]. In every building, the number of floor area is high. Therefore, floor cleaning robots can contribute tremendous services to those buildings.

Navigation of a floor cleaning robot is not the same as a typical robot since its navigation goal is to efficiently

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maximize area coverage. The robot should be capable of perceiving the environment and planing an appropriate trajectory for cleaning. Several research studies have been conducted to develop path planning methods for cleaning robots. A navigation algorithm using an evolutionary approach was introduced in [7]. A circular-shaped vacuum cleaning robot was considered for the development of the path planning algorithm of the cited work. The environment to be cleaned is divided into disk cells for the path planning coverage problem. Although the navigation algorithm is working properly, the area coverage is limited due to its fixed circular shape and the disk cell grid.

In [8], the authors introduced a sensor-based complete coverage path planning (CCPP) algorithm for a cleaning robot in a dynamic environment. A method for coverage path planning (CPP) for extremely large environments was introduced in [9]. It proposed a map decomposition method to split large environments into sub-maps. They have used a spiral path for large unknown environments. It was better if the system could be able to have an optimization algorithm for larger space by considering dynamic navigation. Another limitation of the method is that the robot should not be very small for a large environment otherwise the time required for cleaning is very high. A simulation-based optimization method for scheduling multiple cleaning cycles was proposed in [10].

Energy efficiency and time are major factors to be concerned about a cleaning robot. Therefore, numerous research studies in this niche have been conducted concerning these factors. An online simulation-based energy efficient coverage path planning method for a mobile robot has been introduced [11]. They have considered backtracking for path planning with energy-efficient navigational coverage for the mobile robot. Multiple cleaning robots have been used for area coverage to improve the efficiency of cleaning [12]. They used a bio-inspired neural network model to tackle the area coverage path planning. The model is capable of handling the group of robots for area coverage. Although the time taken from the robots is lesser than a single robot, the cost of deployment is high. A study has been conducted to analyze the performance of conventional cleaning and robot vacuum cleaning [13]. According to their findings, the robot vacuum cleaners can save more energy per unit than manual cleaning machines.

Several reconfigurable robots have been introduced [14]–[17]. Most of them are developing for search and rescue operations, and exploration. Nevertheless, few were proposed for floor cleaning purposes [18], [19]. There are many benefits of using a reconfigurable robot as a cleaning robot. It can change its morphology when obstacles present in a space and can navigate through narrow spaces. Thereby, a reconfigurable floor cleaning robot can increase area coverage which is the main shortcoming of robots with fixed morphologies. Most of the previously discussed robots have fixed morphologies, and those robots are not capable of navigating through narrow spaces. As a solution

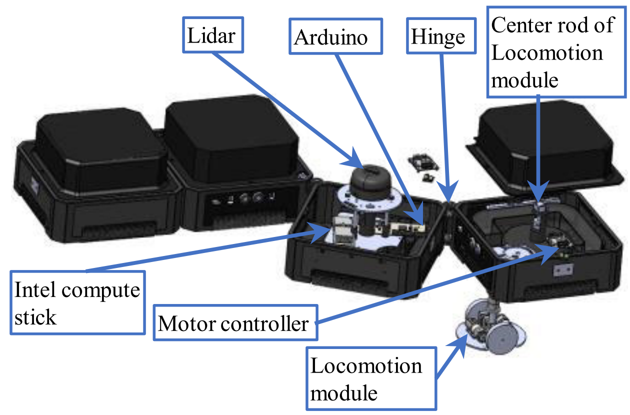


FIGURE 1. **Hardware design of the existing hTetro.**

to this problem, a reconfigurable robot with floor cleaning abilities named hTetro has been introduced [18]. hTetro is a self-reconfigurable modular robot inspired by Tetris. It is capable of changing its morphologies to seven one-sided tetrominoes. In the work [18], hTetro's area coverage has been compared against a commercially available fixed morphology robot. According to the outcomes of the work, hTetro has a higher area coverage than a fixed morphology robot. Furthermore, a floor cleaning robot named hTromo has been introduced with three reconfigurable blocks [20]. The authors have validated the application of three tiling theorems for tackling the area coverage by hTromo robot. The key requirements of cleaning robots are area coverage, energy usage and the time consume for cleaning [21]. Therefore, much research has been conducted to improve area coverage of tiling robots. A complete coverage path planning method has been introduced for a reconfigurable floor cleaning robot combining tiling theory and genetic algorithm [22]. The robot is capable of navigation in the shortest distance path with minimum grid coverage time without revisiting the previously approached grid cells. This approach is useful in saving energy and time.

In the previous work on tiling robots [18], [22]–[24] the robots are operated with only with a limited number of morphologies. Moreover, the existing area coverage algorithms for tiling robots consider a less number of morphologies for the reconfiguration. The area coverage and path planning are conducted through tiling theory by considering only a fixed number of shapes. In these methods, the obstacles and the walls are assumed as square shapes although it is not true for most of the real-world cases. As a result of this assumption, there can be uncovered areas when the tiling based coverage is considered.

This paper introduces a novel hTetro-Infi, which is capable of having uncountable morphologies, to overcome the limitations of the existing tiling robots mentioned above. Feedforward Neural Network (FNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are used to synthesize appropriate morphologies to improve area coverage by considering shapes of obstacles. The formation of hTetro-Infi, which

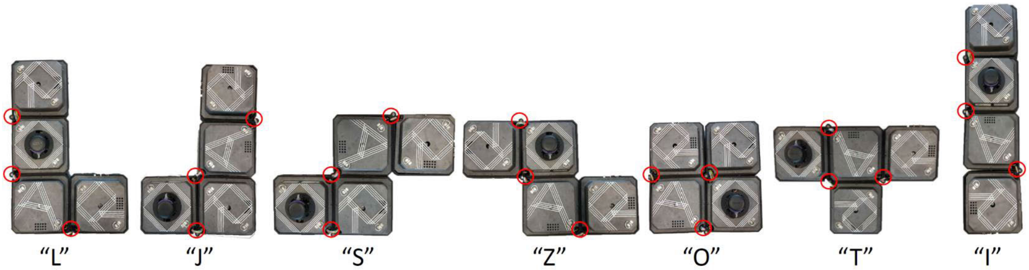


FIGURE 2. Seven shapes of hTetro considered for tilling theory based coverage planing.

considers an infinite number of reconfigurable morphologies without limiting the number of reconfigurable morphologies to a few, is the novel contribution of this paper with respect to the state of the art. Section II briefs about the robot platform. The proposed hTetro-Infi is presented in Section III with due attention to the rationale and the method proposed for synthesizing morphologies. Particulars on the validation of the proposed concept are discussed in Section IV. Section V provides the concluding remarks.

II. ROBOT PLATFORM

The existing hardware platform of hTetro consists of four blocks with each consist of a cleaning module. Figure 1 shows the hardware components of the robot. Each block is connected to another block by a free hinge. Thereby, three free hinges are included in the robot. These hinges facilitate the relative motion between blocks that supports the reconfiguration into different morphologies. Each hinge angle can be varied from 0° to 180°. The dimensions of each block are 250 mm x 250 mm x 130 mm (length x width x height). Every block is included with a differential drive wheel unit powered by two 12 V DC motors combined with omnidirectional wheels. The central rod, which can be freely rotated, is connected with these locomotion modules. Therefore, the steering angles of a locomotion module can be changed by the differential drive mechanism. A 2D LiDAR is used to map the surrounding environment as a 2D map which is utilized for navigation, localization, and planing area coverage. Intel compute stick is deployed to perform high-level tasks such as path planning and mapping. The Arduino mega controller communicates with the Intel compute stick and takes necessary low-level control actions such as motor control. Other subcomponents of the robot are motor drivers, absolute encoders mounted on top of each locomotion module, and batteries. The same hardware platform (i.e., hardware platform of hTetro) is expected to be used for the concept of hTetro-Infi, which considers an infinite number of morphologies, with minor alterations such as fixing encoders for hinges and modifications of low-level control algorithms.

III. hTetro-INFI

A. RATIONALE BEHIND THE PROPOSED METHOD

The rationale behind the proposed hTetro-Infi is explained based on conventional hTetro which is one of the existing tiling robots. The existing work on hTetro considered that hTetro can have only seven distinct shapes, and the shapes are 'O', 'T', 'Z', 'S', 'I', 'L' and 'J' [22]–[24]. The morphologies that are mimicked by the conventional hTetro is shown in Figure 2. These seven morphologies are created by changing i^{th} hinge angle ($\theta_i \in \{0, \pi/2, \pi\}$) for $i = 1, 2, 3$. Typically, polyomino tiling theory is followed to generate shapes for filling a given space. Therefore, initially, an environment to be cleaned is divided into a grid such that each cell is equivalent to the size of a block of hTetro. An environment to be cleaned can be occupied by many objects which can have heterogeneous shapes. The environment shown in Figure 3(a) can be considered as an example where there is an oval-shaped object. In previous work on hTetro, any grid cell partially occupied by any object is assumed as the grid cell is completely occupied to facilitates the application of tilling theory. The grid map corresponding to the example is shown in Figure 3(b) where black cells are considered as occupied areas.

After generating the occupancy grid map for tilling, the robot generates tiling sets for free space by following polyomino tiling theory as Figure 3(c). The main shortcoming of the existing methods is that there will be an uncleaned space due to the fact the partially filled grid cells are considered as fully occupied. The uncleaned area in the example scenario is visualized in Figure 3(d). The main objective of a reconfigurable floor cleaning robot is to improve area coverage. However, hTetro with only seven shapes fails to realize the maximization of area coverage in situations where an environment is occupied by objects with heterogeneous shapes. Thereby, the reconfigurability of hTetro beyond seven morphologies could solve this problem. Moreover, hTetro should not be limited to the seven one-sided tetrominoes and hTetro should be considered with an infinite number of morphologies. hTetro with infinite morphologies is considered as hTetro-Infi (which is proposed in this paper).

The operation of the proposed hTetro-Infi can be explained with the aid of the previously discussed example situation. hTetro-Infi perceives the exact shape of an occupied object through sensory and map information when it reaches near to the object as depicted in Figure 3(e). After that, hTetro-Infi changes its morphology to match the outer shape of the object by changing its i^{th} hinge to any θ_i such that $\theta_i \in [0, \pi]$. The way of transforming its morphology to match the shape of

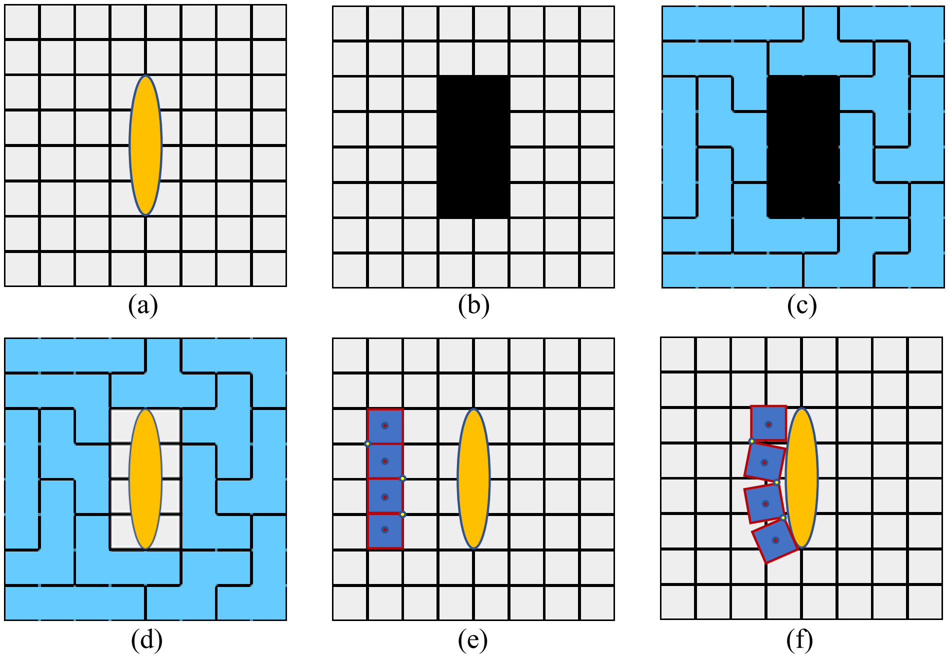


FIGURE 3. The figures describe the area coverage of hTetro (i.e., one of the existing tilling robots) and hTetro-Infi (i.e., the concept proposed in this paper) in an example situation where the environment is occupied by an oval-shaped object. (a): An environment occupied with an oval-shaped obstacle divided into a grid, (b): The environment considered by hTetro for cleaning (the area going to be cleaned is represented in white). (c): The area covered by applying tiling theory (previous work of hTetro follows this methodology), (d): The area which will not be cleaned by hTetro is represented in white. The area that will be covered by the robot is represented in blue. (e): hTetro-Infi (the concept proposed in this paper) observes the obstacle for synthesizing an appropriate shape to approach the object. (f): hTetro-Infi approached the obstacle with the synthesized shape to improve the coverage.

an object is explained in Section III-B. Then, hTetro-Infi will approach the object as depicted in Figure 3(f) which covers the area uncleaned by the existing methods (conventional hTetro). Thereby, hTetro-Infi can increase area coverage by changing its hinge angles per the shape of an object. The robot can mimic an infinite number of shapes by changing its hinge angles to any value in their ranges. Therefore, the proposed concept is introduced as hTetro-Infi. The overall process of the proposed hTetro-Infi is summarized in Algorithm 1.

B. PRINCIPLES OF SYNTHESIZING AN APPROPRIATE MORPHOLOGY

The main improvement of hTetro-Infi over the existing approaches is that hTetro-Infi is capable of adapting its morphology to match the outer shape of an object that it encounters during cleaning. The map built using LiDAR information is used to determines the locations of objects. The robot covers the area to be cleaned based on the tilling theory until it reaches the proximity of an object. The robot maintains a gap of one cell from the area that is considered as occupied as shown in Figure 4. It should be noted that the area considered as occupied may not be completely occupied. Then, the robot perceives the shape of the object as the displacement along X_1 axis between the center point of each block (i.e., C_1, C_2, C_3, and C_4) to the obstacle. The distances are marked as d_1, d_2, d_3, and d_4 respectively. The distances, d_1, d_2, d_3, and d_4 can be obtained from map and LiDAR information. The distance and angular resolutions of the LiDAR in hTetro are

Algorithm 1 Area Coverage

```
input  : Metric Map
output: Coverage Plan
initialization;
Divide the map into a grid;
Generate the occupancy grid map;
Generate the tiling set;
Starting coverage;
while ! coverage completed do
    Navigation;
    if Near new occupied area then
        Cover_object();
    end
end
Function Cover_object():
    Stay away one grid from the occupied area;
    Perceive the exact shape of the obstacle;
    Synthesize an appropriate morphology;
    Approach to the object;
    Return back;
end function
```

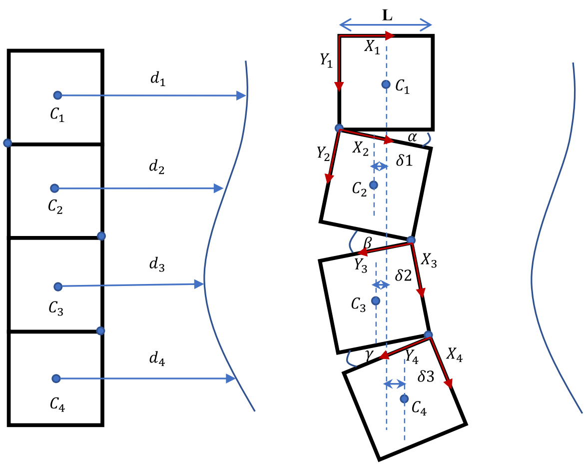


FIGURE 4. **The robot perceive the shape of an object as distance from the center points C_1, C_2, C_3, and C_4 to the obstacle along X_1 axis. The distances are labeled as d_1, d_2, d_3, and d_4 respectively. The hinge angles are symbolized as α, β and γ. The frame axes of blocks are considered as (X_1, Y_1), (X_2, Y_2), (X_3, Y_3) and (X_4, Y_4) for the block 1, 2, 3 and 4 respectively. The offsets required to be maintained for the block 2, 3 and 4 to match the object are symbolized as δ_1, δ_2 and δ_3.**

0.5 mm and 0.9° respectively. Therefore, these distances can be measured with sufficient accuracy in practical usage. The first block is taken as the reference frame for the other three blocks. To match the outer shape of an object, the centers of the robots' blocks should replicate the outer shape of the obstacle. This can be achieved by varying the hinge angles, α, β, and γ in such a way that each block needs to maintain an offset with the reference block. The required offsets are considered as δ_1, δ_2, and δ_3. The offsets can be calculated for a particular scenario as given in (1). The offsets are measured along X_1 axis.

$$\begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \end{bmatrix} = \begin{bmatrix} d1 - d2 \\ d1 - d3 \\ d1 - d4 \end{bmatrix} \tag{1}$$

The coordinate frames of blocks are notated as (X_1, Y_1), (X_2, Y_2), (X_3, Y_3) and (X_4, Y_4) for block 1, 2, 3, and 4 respectively. Homogeneous transformation matrices from frame {1} to frame {2} (i.e., ${}^1_2T$) from frame {2} to frame {3} (i.e., ${}^2_3T$), and from frame {3} to frame {4} (i.e., ${}^3_4T$) are given in (2), (3), and (4).

$${}^1_2T = \begin{bmatrix} cos(\alpha) & sin(\alpha) & 0 \\ sin(\alpha) & cos(\alpha) & L \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$${}^2_3T = \begin{bmatrix} sin(\beta) & -cos(\beta) & L \\ cos(\beta) & sin(\beta) & L \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$${}^3_4T = \begin{bmatrix} cos(\gamma) & sin(\gamma) & L \\ -sin(\gamma) & cos(\gamma) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

The center position of i^{th} block with respect to the frame {1}, ${}^1C_i$ is given in (5), where ${}^iC_i$ is the center position of i^{th} block with respect to i^{th} frame. ${}^1C_i$ and ${}^iC_i$ are matrices that have the format given in (6), where x_i, y_i, and z_i represent the translations to the center position along X, Y, and Z axes of the frame of interest. The component along the X-axis of frame {1} (i.e., along X_1) is the factor of interest for establishing the relationship between the offsets of the centers and hinge angles. The relationship between the offsets and the center positions of j^{th} blocks is given in (7). The relationship between the hinge angles and the offsets of the center points can be obtained from using (2) to (7).

$${}^1C_i = \prod_{k=1}^{i-1} {}^{k}_{k+1}T \ {}^iC_i \quad \text{for } i = 2, 3, 4 \tag{5}$$

$${}^1C_i = \begin{bmatrix} {}^1x_i \\ {}^1y_i \\ 1 \end{bmatrix}, \quad {}^iC_i = \begin{bmatrix} {}^ix_i \\ {}^iy_i \\ 1 \end{bmatrix} \tag{6}$$

$$\delta_j = {}^ix_{j+1} - {}^1x_1 \quad \text{for } j = 1, 2, 3 \tag{7}$$

The robot can perceive d_1, d_2, d_3 and d_4 from the sensory information. Thereby, the required offsets to synthesize a morphology for a particular situation can be calculated from (1). Then, the required hinge angles (α, β, and γ) to synthesize the morphology have to be obtained using the established relationships between hinge angles and the offsets. Moreover, three hinge angles (α, β, and γ) need to be calculated for given three offsets (δ_1, δ_2, and δ_3) in a scenario. Nevertheless, it would not always be possible to find the hinge angles that satisfy the required offsets since the required offsets might not be achieved by the robot due to the hardware limitations. Furthermore, the problem could not be deduced to an inverse kinematic problem of a manipulator end-effector positioning since, in this specific case, the positioning of intermediate locations (offsets of three centers) has to be also considered instead of merely the end effector positioning. In addition to that, imprecision sensory information induces uncertainty to the system. Therefore, relying on an analytical/geometrical approach is not feasible for realizing the required goal of the proposed concept. On the other hand, approaches based on soft computing techniques such as neural networks and neuro-fuzzy systems have been proven to cope well in similar sorts of situations [25]–[27]. Moreover, solutions based on approximators/soft computing, which consider the problem holistically, would have greater potential. Therefore, a Feedforward Neural Network (FNN) and Adaptive Neuro-Fuzzy System (ANFIS) have been used to synthesize the appropriate hinge angles per the shape of an object.

C. FEEDFORWARD NEURAL NETWORK (FNN) APPROACH

An Artificial Neural Network (ANN) can be described as a parallel distributed processor build up with simple processing units that can accumulate knowledge through learning. The problem of synthesizing an appropriate morphology is related to a combination of multivariate and nonlinear

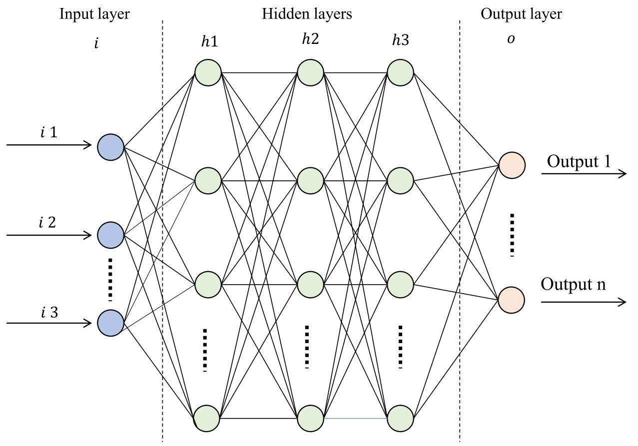


FIGURE 5. The architecture of a feedforward neural network (FNN).

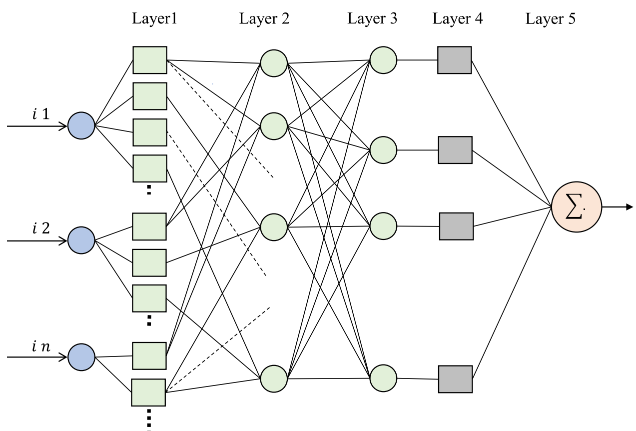


FIGURE 6. The architecture of an adaptive neuro fuzzy inference system (ANFIS).

modeling. ANN can be used as a solution for this problem due to its robustness and capability of surface approximation. Therefore, a Feedforward Neural Network (FNN) is examined as one of the options to obtain hinge angles to synthesize an appropriate morphology in this work. Figure 5 illustrates the general architecture of an FNN. The input layer, hidden layers, and output layer are the main three types of layers present in an FNN. The input and output layers each contain only one layer of neurons while hidden layers may contain one to few layers depending on the case. The numbers of neurons in the input and output layers are equivalent to the number of inputs and outputs respectively. The number of hidden layers and the number of hidden neurons are typically determined trial and error based on performance. The offsets, δ_1, δ_2, and δ_3 are taken as the inputs, and the outputs are the hinge angles α, β and γ to synthesize an appropriate morphology. The artificial neurons in different layers are interconnected through weights. The weights are adapted in the training to map inputs (i.e., the offsets of center positions of the blocks) and outputs (i.e., corresponding hinge angles). Each artificial neuron has an activation function that maps its inputs with its output. Generally, nonlinear activation functions such as tangent sigmoid and logarithmic sigmoid are used as activation functions of FNN [28].

According to the universal approximation theorem, a single hidden layer FNN with a finite number of neurons can approximate continuous functions on compact subsets of $\mathbb{R}^n$, where n is the number of inputs [29]. There is no general rule to define the best FNN architecture configuration for a given set of inputs and outputs. Typically configuration of the architecture such as the number of hidden neurons is decided trial and error based on the performance and requirements. The training was conducted using Levenberg-Marquardt (LM) backpropagation algorithm [30] considering the Mean Squared Error (MSE) as the performance measure. The LM technique was selected since it has a second-order convergence rate and high efficiency for FNN [31].

D. ADPATIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) APPROACH

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid artificial intelligent method that combines a fuzzy inference system and an Artificial Neural Network. Although several types of neuro-fuzzy hybrid systems are available, ANFIS introduced by Jang [32] is the most widely used method. An ANFIS can be considered as an ANN based on Takagi–Sugeno fuzzy inference system. Since ANFIS is a hybrid method of neural networks and fuzzy logic principles, it possesses the benefits of both techniques. More specifically, ANFIS has the learning capability of ANN and the decision making ability of fuzzy logic. ANFIS is considered to be a universal approximator since the reasoning mechanism of ANFIS resembles a set of learnable fuzzy if-then rules that are capable of approximating nonlinear functions [33].

The architecture of the proposed ANFIS is shown in Figure 6. It consists of five layers. The inputs of the ANFIS are the offsets of the centers of the blocks (i.e., δ_1, δ_2, and δ_3). Layer 1 is the fuzzification layer that fuzzifies the inputs of ANFIS utilizing the membership functions represented in each node of layer 1. The number of nodes per input depends on the number of fuzzy sets considered for representing the input space. Layer 2 is the fuzzy rule layer. Each node in this layer corresponds to a single fuzzy rule, and the output of a node is the firing strength of the corresponding rule. The algebraic product operator is used as the T-norm fuzzy operator to obtain the firing strength from the inputs to a node in this layer. Layer 3 is called the normalizing layer since it normalizes the firing strength of each rule by diving each from the total firing strength. Nodes in layer 4 represent consequents parameters (i.e., singleton output sets of a Takagi–Sugeno fuzzy inference system). Layer 5 computes the crisp output of the ANFIS by considering the summation of incoming signals. The problem considered in this paper should have three outputs which are the corresponding hinge angles to synthesize an appropriate morphology. Therefore, multiple ANFIS are combined as a coactive-ANFIS [34] to facilitate the multiple outputs. Therefore, the outputs of this coactive ANFIS are the corresponding hinge angles (i.e., α, β, and γ) for a given set of offsets. The hybrid learning rule proposed in [32] has been used for the training of this ANFIS. The hybrid learning rule uses a combination of backpropagation to compute input membership function parameters, and least-squares estimation to compute output membership function parameters.

IV. RESULTS AND DISCUSSION

A. TRAINING AND TESTING OF FNN AND ANFIS

The data set required for training, validation, and testing of the FNN and the ANFIS was generated through the relationship established between hinge angles (i.e., α, β, and γ) and the corresponding offsets of centers (i.e., δ_1, δ_2, and δ_3). The relationships given in (2) to (7) were used for this purpose. Moreover, the offsets corresponding to a set of hinge angles were calculated for all the possible combinations of hinge angles. Nevertheless, the step size of a joint angle was considered as 5° to avoid the generation of an excessively large data set, which may lead to a very high data generation time and training time. In this way, a data set consists of 13357 distinct entries that represent relationships between the offsets corresponding to joint angles. The data set was randomly divided into 3 distinct subsets for training, validation, and testing. 70% of data was used for training while 15% each for validation and testing. When training the FNN and the ANFIS, the offsets and hinge angles are used as the inputs and the outputs respectively since the goal of the work was to develop a mechanism to synthesize the joint angles to have the offsets required for a particular scenario. The set of training data consists of data in relation to morphology configurations that can be achieved by the robot. Therefore, inputs heavily deviated from the possible morphology configurations of the robot may lead to undesirable output results such as hinge angle values that are not compliant with the joint ranges. (The ways for coping out of the range hinge angles synthesized by FNN and ANFI are given in Section IV-D)

Three different configurations of FNNs were analyzed by considering Root Mean Square Error (RMSE) as the performance indicator to identify the most suitable configuration of FNN for this specific problem. The maximum number of epochs was limited to 1000, and the training was terminated either decrease of performance gradient below minimum threshold or increase of generalization error (when error for validation data is increased) is observed. After the training, the trained FNNs were evaluated by using the set of testing data. RMSEs observed for the three configurations of FNNs are given in Table 1 along with their configuration details. The parameter number (i.e., N_P) of each network is given to the better comparison of the complexity level of each network. Mean execution time (i.e., t) of each network has been calculated from running the proposed models implemented in MATLAB on a laptop with the Intel Core i7-9750H processor and 16 GB memory. Parallel processing was not used in this regard. Since t of the FNNs are in the order of microseconds, the execution times of these models would not cause overhead for the robot in online operation. In contrast, the compute stick of the robot is expected to have a lower specification than the tested environment (compute stick: Intel Core m5-6Y57 Processor and GB). However, the execution time would not be intensively increased in such a way that it hinders the online operation after deployment in a compute stick. FNN-2, which had 100 hidden neurons, received the lowest RMSE (7.28) for testing data. Therefore, the best performance was observed from FNN-2 among other FNNs. The execution time, t of FNN-2 is 0.0393 ms.

TABLE 1. Comparison of the trained networks.

Network	Configuration details	N_P	RMSE	t (ms)
FNN-1	10 hidden neurons	73	9.94	0.0377
FNN-2	100 hidden neurons	703	7.28	0.0393
FNN-3	1000 hidden neurons	7003	7.48	0.1334
ANFIS-1	3 triangular fuzzy sets per input	405	10.81	0.7652
ANFIS-2	5 triangular fuzzy sets per input	1635	7.82	2.4798

In the case of ANFIS, two different configurations were considered by altering the number of fuzzy sets used per an input membership function. Three and five triangular fuzzy sets per input were used in ANFIS-1 and ANFIS-2 respectively. The initial membership functions of the ANFISs were generated through grid partitioning. In general, clustering-based methods for initializing ANFIS such as subtractive clustering, would lead to simpler fuzzy structures than grid-partitioning. However, when using grid-partitioning to generate the initial fuzzy membership function, the corresponding fuzzy rules are uniformly generated. Moreover, the input space is smoothly analyzed. Therefore, grid-partitioning is preferred over the other methods when the dimension of the input space is small [35]. The number of inputs of the proposed ANFIS is 3, which is a low number that leads to a simple structure even though grid partitioning was used. Therefore, grid-partitioning opted for the initialization of ANFIS. Then, these initial fuzzy membership functions were tuned by training through the hybrid learning rule. The training has been done for both ANFISs considering the maximum number of epochs as 100. Nevertheless, the training was terminated when an increase of the error for validation data was observed to avoid overfitting. RMSEs observed for the two ANFISs are also given in Table 1. ANFIS-2, which had 5 triangular fuzzy sets per input, was selected as the best among two ANFISs since it had the lowest RMSE for testing data. The execution time, t of ANFIS-2 is comparatively more substantial than that of other networks. Nevertheless, the mean execution time was 2.479 ms, which is negligible with respect to the operation time of the robot.

B. BEHAVIOR OF SYNTHESIZING MORPHOLOGIES

The behavior and overall operation of hTetro-Infi are explained based on the situation depicted in Figure 7, where the robot approaches an object from the four principal directions. In this situation. The object has dissimilar outer shapes

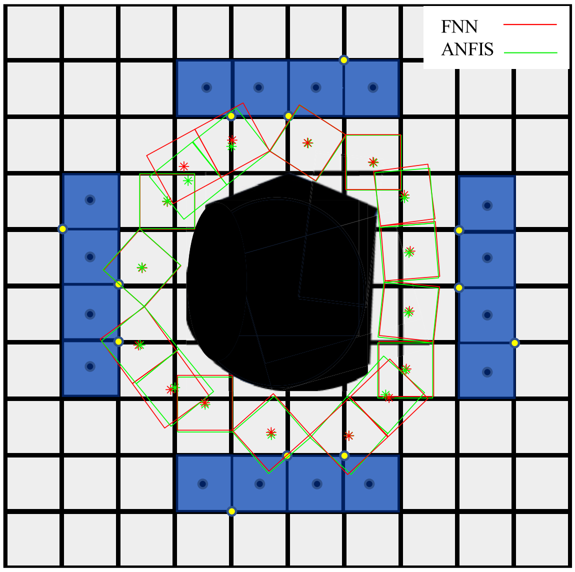


FIGURE 7. hTetro-Infi approaching an object in different directions.

TABLE 2. Variation of synthesized hinge angle when the robot approaches the object in different directions.

Direction	Distance from centers (cm)				Hinge angles (°)					
					FNN			ANFIS		
	d_1	d_2	d_3	d_4	α	β	γ	α	β	γ
Left	54.6	43.1	41.7	54.6	41.6	77.6	0.0	41.7	80.9	0.0
Up	50.3	41.4	41.4	50.0	32.8	61.5	0.0	33.2	71.2	0.8
Right	50.9	49.5	48.9	47.4	6.2	10.8	2.9	6.1	10.8	0.0
Down	54.8	41.0	39.4	48.9	48.2	91.3	0.8	49.2	97.3	0.0

from the perspective of the approaching directions. Hence, the robot had to approach the object by synthesizing an appropriate morphology for each approaching direction to improve area coverage. A MATLAB based simulation was conducted to verify and analyze the behavior and overall operation of hTetro in similar situations. The FNN network and the ANFIS, which had the best performances, were used for synthesizing morphologies for hTetro-Infi. The operation of hTetro with FNN and hTetro with ANFIS were independently considered. The results related to the synthesizing of the morphologies in this situation are given in Table 2.

hTetro-Infi approaching the obstacle from the left of the object was considered as the first instance. Initially, hTetro-Infi maintained a gap of one cell from an object before changing its morphologies. The distances along X_1 axis from the center of each block of the robot to the occupied object were determined by the robot. The obtained distances were $d_1 = 54.6$ cm, $d_2 = 43.1$ cm, $d_3 = 41.7$ cm, and $d_4 = 54.6$ cm. Then, the robot calculated the offsets to be maintained with centers of the blocks (i.e., δ_1, δ_2 and δ_3). The required hinge angles to synthesize a shape to match the object were done by the FNN (for hTetro-Infi with FNN) or ANFIS (for hTetro-Infi with ANFIS). In the event of hTetro-Infi with FNN, the hinge angles were determined as $\alpha = 41.6°$, $\beta = 77.6°$, and $\gamma = 0.0°$ by the FNN. After that, it changed its morphology considering the synthesized hinge angles. Then, it approached the obstacle with the synthesized shape. As shown in Figure 7, hTetro-Infi was able to synthesize a morpholgy that can match with shape of the object. In the case of hTetro-Infi with ANFIS, the hinge angles were determined as $\alpha = 41.7°$, $\beta = 80.9°$ and $\gamma = 0.0°$ when the robot was approaching from the left. From those generated hinge angles the robot was able to change the morphology in accordance with the shape of the object. As similar to the event of FNN, then the robot approached the object.

Similarly, hTetro-Infi (with FNN and ANFIS) was able to synthesize an appropriate morphology to match with the shape of the object when approaching from the principal directions as shown in Figure. This behavior validates that the proposed hTetro-Infi can synthesize appropriate morphologies when approaching an obstacle from different directions; subsequently, hTetro-Infi covers an additional amount of area that would not be covered from existing methodologies for tiling robots.

C. EVALUATION OF AREA COVERAGE

The goal of the work was to improve the area coverage by considering an infinite number of morphologies for hTetro-Infi. Therefore, area coverage of hTetro-Infi (i.e., the concept proposed in this paper) was evaluated against one of the existing tiling robots. The FNN network and the ANFIS, which had the best performances, were used for evaluating the effect on area coverage. Typically, objects with heterogeneous shapes can be occupied in a floor area that going to be cleaned by a floor cleaning robot. Therefore, eight distinct cases, where the floor areas are occupied by objects with heterogeneous shapes, were considered for the evaluation. Both FNN and ANFIS techniques for hTetro-Infi were used for each case for synthesizing an appropriate shape to match the occupied object. The simulations were conducted using MATLAB. Figure 8 depicts the arrangements of the eight cases used for the evaluation. The area that cannot be covered from each of the configurations of the robot were obtained to evaluate the performance improvement of the proposed approaches (hTetro-Infi with FNN and hTetro-Infi with ANFIS) with respect to the existing methods (hTetro with only seven morphologies). The hinge angles (α, β, and γ) synthesized by hTetro-Infi for the corresponding distances from the centers to the obstacle (d_1, d_2, d_3, and d_4) in each case are given Table 3 including the amount of uncovered area (U. Area).

hTetro-Infi (both FNN and ANFIS) had a lower uncovered area with respect to hTetro in all the test cases. The means of the uncovered area of these cases for hTetro-Infi and hTetro are emphasized in Figure 9 (a) along with error bars. A one way ANOVA test was conducted to evaluate the statistical significance of the results obtained for area coverage. The one way ANOVA test confirms that at least one mean is significantly different from others ($F_{7,21} = 24.88$,

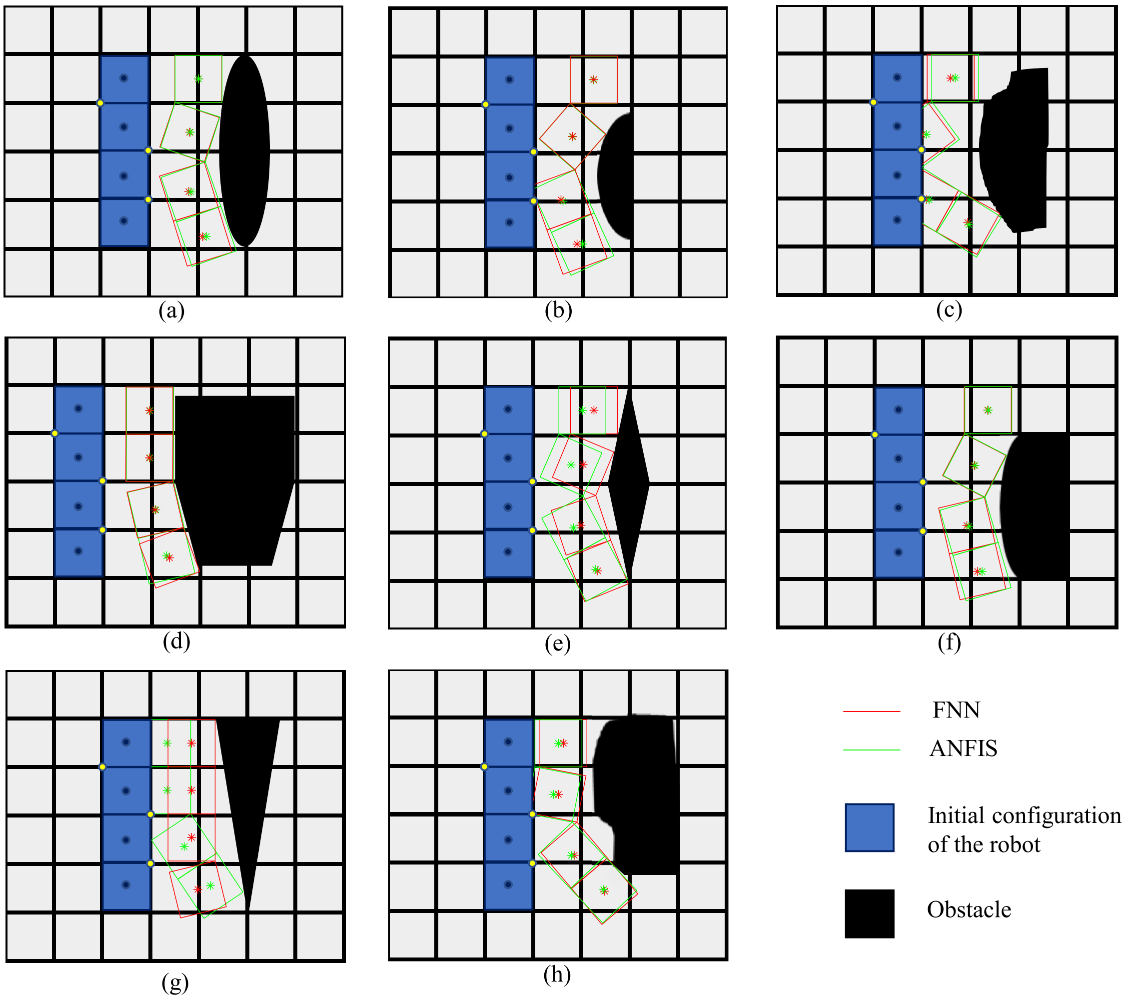


FIGURE 8. Arrangements of the test cases for the evaluation of area coverage.

$P = 0.00$). Since there is a significant difference in at least one, Tukey pairwise comparison test was conducted to find out the pairwise differences. The test result of Tukey pairwise comparison test is shown in Figure 9 (b). According to the test result, there is no significant difference between hTetro-Infi with FNN and hTetro-Infi with ANFIS. In contrast, there is a significant difference in the mean uncovered area of hTetro from that of both hTetro-Infi configurations. Moreover, a significant reduction of the uncovered area could be observed from hTetro-Infi compared to hTetro. Furthermore, the reduction of the uncovered area by hTetro is huge since Cohen's d value of 2.96 can be observed from results (since Cohen's d value greater than 2.0 is considered as a huge effect [36]). Therefore, the evaluation validates that the uncovered area is significantly less for hTetro-Infi (proposed in this paper) compared to hTetro (existing approaches), and this reduction of the uncovered area is huge. Moreover, it can be concluded that the proposed hTetro-Infi can significantly improve the performance from the perspective of area coverage compared to the existing tiling robots with limited number of morphologies.

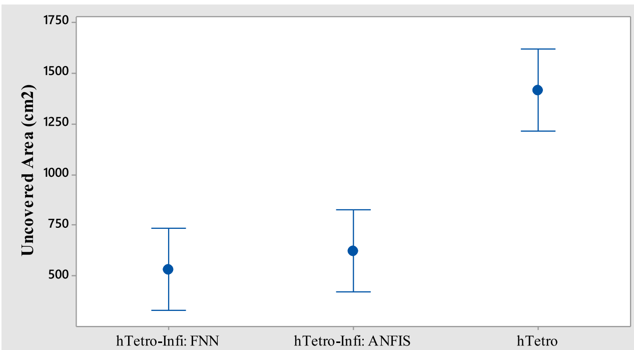
D. DISCUSSION

The proposed hTetro-Infi was compared against hTetro, which is one of the state of the art tilling robots, to evaluate the area coverage. hTetro was selected for the comparison with the proposed hTetro-Infi since both robots possess a similar hardware arrangement. Moreover, the hardware structure of both robots is almost the same. Thereby, the usage of a robot with equivalent hardware for comparison of performance eliminates the bias that might be arisen due to the hardware differences. In addition to that, hTetro is widely appeared in research work compared to the other tilling robots. Thereby, the comparison of hTetro-Infi against hTetro can be deemed as a comparison of hTetro-Infi against the state of the art tiling robots.

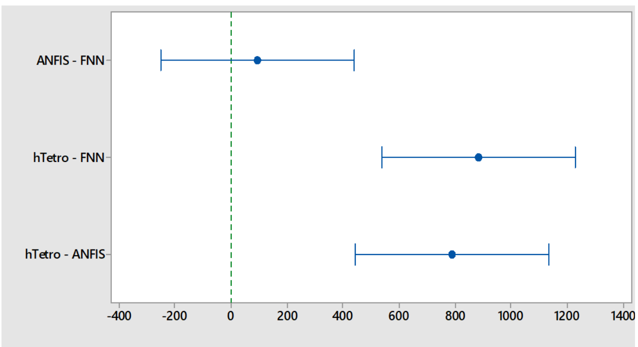
The test environments for the comparison were selected by considering the typical shapes of objects observed in floor areas such as pillars and furniture. However, the situations with multiple scattered objects were not considered for the test cases since the appropriate morphology synthesizing for situations with multiple scattered objects is not addressed within the scope of the paper. The work proposed in this

TABLE 3. Results of area coverage evaluation.

Case	hTetro-Infi												hTetro
	Distance from centers (cm)				FNN				ANFIS				U. Area (cm^2)
					Hinge angles (°)			U. Area (cm^2)	Hinge angles (°)			U. Area (cm^2)	
	d_1	d_2	d_3	d_4	α	β	γ		α	β	γ		
a	52.7	47.9	47.9	52.7	18.8	36.0	0.0	603.7	17.9	37.2	0.0	538.4	1518.3
b	62.5	51.2	45.8	51.8	40.9	60.8	0.0	637.5	41.1	65.8	0.0	566.1	951.8
c	57.7	42.6	43.2	60.4	53.4	114.3	0.0	811.5	53.8	111.9	0.0	745.2	1064.0
d	49.7	49.7	52.4	59.2	00.3	13.3	7.5	251.6	0.3	13.5	0.0	237.8	1604.6
e	58.6	52.7	52.7	57.2	22.6	41.1	3.5	308.7	23.5	51.7	0.0	803.6	1892.9
f	62.5	55.4	51.8	55.4	27.4	40.6	0.0	337.3	27.3	43.4	0.0	276.9	1243.9
g	47.9	51.5	55.1	59.5	0.0	0.0	13.7	732.2	0.0	33.8	0.0	1124.2	1642.2
h	45.8	43.2	50.9	62.5	11.1	51.5	0.0	575.8	10.8	54.2	0.0	707.4	1386.7



(a)



(b)

FIGURE 9. **(a) Variation of mean uncovered area in different configurations of the robot. The error bars are drawn to represent the standard error. (b) Turkey simultaneous 95% confidence intervals plot. If an interval does not contain zero, the corresponding means are significantly different. The labels are defined as follows; hTetro: the robot limited to seven morphologies, hTetro-Infi FNN: the FNN based method proposed in this paper, and hTetro-Infi: the ANFIS based method proposed in this paper.**

paper is the first paper in a niche of research that considers an infinite number of reconfigurable morphologies for a tiling robot instead of a limited number of reconfigurable shapes utilized by the state of the art methods. Therefore, it is reasonable to limit the scope of this work to consider situations with single objects, and the extension of the proposed method for situations with multiple scattered objects is proposed for future work.

According to the outcomes of the test cases for the evaluation of area coverage, both configurations of hTetro-Infi (i.e., with FNN and with ANFIS) did not demonstrate any distinct in the performance of area coverage. Nevertheless, there can be slight differences in the operation due to their inherent behavior. An ANFIS is a human interpretable and explainable architecture where an FNN is not. This interpretable behavior allows the amendment of a trained ANFIS based on expert knowledge to have desired control behavior such as limitation of the output space. In the case of the FNN, the FNN might synthesize hinge angles that could be out of the upper and lower bound of the respective hinge angles in some scenarios. Therefore, the hinge angle controller needs to take care of this issue to curtail the operation of the hinges within the limitation to ensure the safety of the robot. In contrast, an output space of the ANFIS could be configured to a fixed range, and the hinge angles synthesized by the ANFIS is always with the operational range of the respective hinges. Thereby, the usage of ANFIS would reduce the overhead of post-processing of the synthesized hinge angles to curtail them within the operational ranges.

In this paper, a novel method for synthesizing an appropriate shape to match an object, which is required for realizing the consideration of an infinite number of morphologies, has been introduced. The possibility of improving the area coverage of a tiling robot considering an infinite number of morphologies for the reconfiguration (instead of a limited number of morphologies) has been proven through the proposed method of synthesizing morphologies. In this regard, an existing tetrominoes based tiling robot, hTetro has been used for grounding the proposed concept of consideration of an unlimited number of morphologies to improve the capabilities. Even though the proposed concept is demonstrated using a tetromino based tiling robot, the concept could be extended to any polyform based tiling robot. For example, this concept can be applied to a tromino based tiling robot such as hTromino [20] with few adaptations. hTromino has only 3 blocks yielding to only two hinges (less than the case of this paper). Therefore. the concept proposed in this paper should be tailored to the reduced number of hinges. Similarly, the proposed concept could be extended for a pentomino based robot by considering its addition hinge (pentomino based robot will have 4 hinges). Therefore, the concept proposed in this paper could easily be tailored to a tilling-theory based reconfigurable floor cleaning robot with any polyform shapes.

The implications of the proposed method mentioned above have been concluded based on simulation results. The simulation results have been obtained by considering the real parameters of the robot hardware. Therefore, the simulation outcomes would not heavily deviate from real-world experiments since the real parameters of the hardware platform is utilized for the simulation. Furthermore, this paper is the first paper in a line of research that considers an infinite number of morphologies for reconfiguration of a tiling robot instead of a limited number for improving the area coverage. Moreover, this paper could be lined up as a proof of concept in this new research direction. Therefore, the implications concluded based on the simulation results are still useful for state of the art. The same hardware platform of hTetro presented in Section II is expected to be used for the concept of hTetro-Infi, which considers an infinite number of morphologies, with minor alterations such as fixing encoders for hinges and low-level control algorithms. The process of implementing the proposed concept of hTetro-Infi by facilitating the necessary hardware and low-level control modifications to the existing hTetro is currently underway. Conducting real-world experiments with the hardware platform is expected to be performed in the next phase of the work.

The considered hinge arrangement of the robot has one hinge on one side (i.e., α) and two hinges on the other side (i.e., β and γ). Thereby, when the robot's morphology needs to be bent toward the side of one hinge, that hinge (i.e., α) takes the responsibility. In contrast, both β and γ take responsibility when the robot needs to be bent toward the side of two hinges. However, the effect of β is comparatively higher in the case of ANFIS where it leads to non-movement of the third hinge angle (i.e., $\gamma = 0$ in all the considered test cases for the robot with ANFIS). On the other hand, in the case of FNN, the third hinge angle plays a considerable role. In addition to that, the method proposed in this paper is used in conjunction with the existing coverage methods based on tiling theory, where it requires the robot to reconfigure into primitive seven shapes. Therefore, the third hinge (γ) cannot be omitted. However, an analysis on identifying efficient configurations of hinge angles for hTetro-Infi is proposed for future work.

In the scope of this paper, the performance of hTetro-Infi against the state of the art was compared in the perspective of area coverage since it is the most crucial parameter for a floor cleaning robot to measure the performance. Nevertheless, the factor such as energy usage and time taken for accomplishing a cleaning task are also fairly crucial for the performance of a floor cleaning robot. Therefore, the investigation of the performance of hTetro-Infi in the perspectives of other parameters is proposed for future work.

V. CONCLUSION

Floor cleaning is a vital task for maintaining the living standard. Robots have been deployed to handle the floor cleaning to reduce the involvement of human labor. Area coverage is one of the important parameters that measure the performance of a floor cleaning robot. Most of the existing floor cleaning robots have fixed morphologies. The main limitation of the floor cleaning robot with fixed morphology is the low area coverage. Reconfigurable robots have been introduced to improve area coverage. hTetro is one of such reconfigurable robot designed for floor cleaning.

The state of the art approaches for tiling robots consider that a robot can be reconfigured only into a limited number of morphologies. The existing work on tiling robots utilizes tilling theory to solve the coverage problem. The environment is divided into a grid with cell size equal to a block of the robot when applying the tilling theory. Existing methods of tiling robots assume that a grid cell is fully occupied even though it is partially occupied to facilitate the application of tilling theory. This assumption reduces area coverage when the environment is occupied by objects with heterogeneous shapes. Therefore, this paper proposed the novel concept, hTetro-Infi, which can take an infinite number of morphologies to improve area coverage.

The proposed hTetro-Infi is capable of synthesizing an appropriate morphology in accordance with the outer shape of an object. The outer shape of an object is perceived by hTetro-Infi through sensory information. Two different techniques, Feedforward Neural Network (FNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) have been proposed for determining the appropriate hinge angles to synthesize a morphology to match an object. FNNs and ANFISs with different configurations have been trained and compared against each other based on the testing error to find the most suitable configuration for each technique. The FNN with 100 hidden neurons and ANFIS with 5 triangular fuzzy sets per input were chosen as the most suitable configurations.

Area coverage of an existing tiling robot was compared against that of the proposed hTetro-Infi through simulations for evaluating the performance. According to the statistical outcomes, both configurations of the proposed hTetro-Infi (i.e., hTetro-Infi with FNN and hTetro-Infi with ANFIS) can significantly reduce the area that would not be covered by a state of the art tiling robot. Furthermore, this reduction is huge. However, no significant difference between hTetro-Infi with FNN and hTetro-Infi with ANFIS could be observed. Therefore, it can be concluded that both the configuration of hTetro-Infi (i.e, with FNN or with ANFIS) can surpass the state of the art methods of tiling robots (which considers only a limited number of morphologies for reconfiguration) in the perspective of area coverage. These implications have been concluded based on simulation results, and it is expected to conduct the experiments with the hardware of the robot in the next phase of the work.

The capabilities of the proposed hTetro-Infi are limited by the hardware configuration of the robot. For example, the morphologies that could be synthesized by hTetro-Infi is dependent on the arrangement of hinge configurations. Therefore, the investigation of effects on different hinge configuration for hTetro-Infi is proposed for future work. In addition to that, the scope of this work is limited to improving the area coverage by synthesizing appropriate morphologies to match with objects occupied in areas to be cleaned. Moreover, this work does not focus on navigation through narrow areas confined with obstacles with heterogeneous shapes by using the infinite number of morphologies. Therefore, the development of hTetro-Infi to navigate through narrow areas would be a potential future development.

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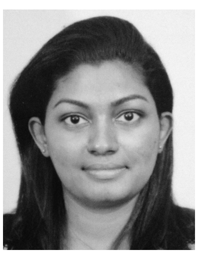

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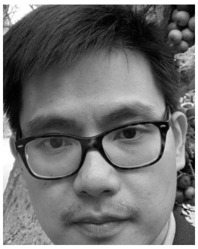

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