Sensory Configurations for Collective Behavior

Abstract—**This paper presents a study on the impact of different robot sensory configurations (morphologies) in simulated robot teams that must accomplish a collective (cooperative) behavior task. The study's objective was to investigate if effective collective behaviors could be efficiently evolved given minimal morphological complexity of individual robots in a homogenous team. A range of sensory configurations are tested in company with evolved controllers for a collective construction task. Results indicate that a minimal sensory configuration yields the highest task performance, and increasing the complexity of the sensory configuration does not yield an increased task performance.**

I. Introduction

An open problem in *cooperative multi-robot systems* [1] is determining, *a priori* the most appropriate sensory-motor configuration (morphology) for individual robots, such that when an automated controller design (behavioral adaptation) method is applied, a robot team evolves a collective behavior to solve a given cooperative task.

This study falls within *Evolutionary Robotics* (ER) [2] research within the larger taxonomy of cooperative multi-robot systems [1], where *Neuro-Evolution* (NE) [3] is used to evolve controllers for a morphologically homogenous team. A popular approach in ER is to employ *Cooperative Co-Evolutionary Algorithms* (CCAs) [4], [5], [6] to co-adapt robot behaviors and morphologies. Such approaches have been successful for finding robot morphologies and controllers specifically suited to accomplishing various tasks and in a range of environments [7], [8], [9], [10], [11], [12], [13], [14], [15].

However, due to the computational complexity and intractable search spaces there has been relatively little research on the co-evolution of morphology and behavior, excluding self-assembly [16] in multi-robot [17] and swarm robotic [18] systems. An alternate approach to using CCAs in ER multi-robot systems is to systematically test a range of robot morphologies in company with controller evolution, in order to ascertain the best team morphology and behavior for a given task and environment. For morphologically homogenous teams such an approach does not entail intractable search spaces or exponentially increasing computational complexity of increasing team sizes and task complexity. Rather, the experimenter must design a set of *morphological parameter tuning* experiments that test a sufficiently diverse yet functional range of robot morphologies. In this case some *a priori* knowledge of the task is assumed.

This study's research objective was to ascertain the most appropriate morphology for a homogenous robot team, that enables the team to efficiently evolve an effective team behavior that solves a collective behavior task. The task was collective construction, where cooperation was required for robots to gather and connect (build a structure) from all resources (blocks) in an environment. Each robot in the team has the same morphology, and an *Artificial Neural Network* (ANN) controller with a variable number of sensory inputs and hidden layer nodes and a fixed number of motor outputs.

Whilst the number of sensory input and hidden nodes and sensor ranges were determined by the experimenter, the ANN connection weights and inter-layer connectivity was adapted with HyperNEAT [19]. Teams were behaviorally homogenous in that the current fittest ANN controller was copied P times for P robots in a team. Each robot also used the same morphology. HyperNEAT was selected as it has been successfully applied to evolve team behaviors for various tasks including *RoboCup* [20] and multi-agent *Pursuit-Evasion* [21]. Also, HyperNEAT is a generative encoding method, and such methods have been demonstrated as beneficial as they tend to produce regular and modular ANNs with increased learning capacities [22].

In this study, a *collective construction* task [23], which was a variation of *collective gathering* [24] was selected. The task was for robots to search for randomly distributed resources (blocks) in the environment and then move them such that they connected to other blocks in the environment, where the goal was for all blocks to be connected. One block type required cooperation between robots to move, while another could be moved by individual robots. In this case, blocks could be connected to any other in order that a structure be built. However, this is a simplified version of a more complex construction task that requires robots to collectively build a structure via connecting resources in specific ways such that a target structure is built [25].

Potential future applications of finding effective solutions to such a task include construction for exploration and mining in hazardous and remote environments [26], [27], where functional structures and habitats must be built from a set of prefabricated modules without human direction [28], [29].

This study is a preliminary step in producing NE methods that autonomously adapt multi-robot and swarm robotic system behaviors and morphologies such that problem solving collective behaviors are produced for high level user specified goals [30]. This relates to recent research in *collective gathering* and *construction* [25] and *self-assembly* [31], where desired structures are specified by a user and robots adapt their individual behaviours in order to collectively build or self-assemble a desired structure.

A. *Collective Construction Task:*

This task requires a simulated robot team to gather blocks and cooperatively build a structure from gathered blocks in a bounded continuous environment (figure 1). The complexity of this task is equated with the degree of cooperation (number of robots required) to collectively transport blocks and connect them together with other blocks in order to build a structure (resultant from connecting all blocks in the environment). In this research there are two block types, A and B that require one and two robots to transport, respectively. The blocks must

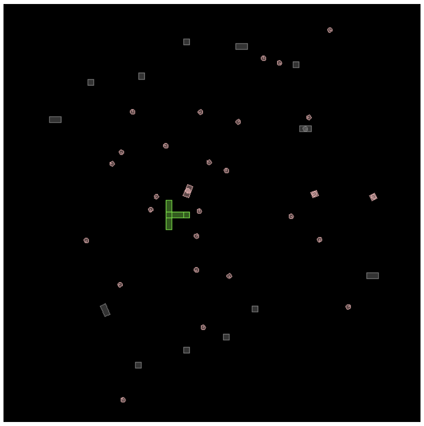

Fig. 1. Collective Construction Task Example: Robots are the circles and blocks as the small (*Type A*) and large (*Type B*) rectangles. The green structure is that which has been built thus far via robots pushing blocks together.

be connected into a structure according to a *construction schema*, that dictates the sequence for how block types must be connected. However, for the testing purposes of this preliminary research the construction schema allows blocks to be connected together in any sequence. Task performance (team fitness) is the number of blocks connected (as a built structure) during a team's lifetime (table I).

II. METHODS

HyperNEAT [19] is an extension of the NEAT (*Neuro-Evolution of Augmented Topologies*) [32] method, where ANNs are indirectly encoded using a CPPN (*Compositional Pattern Producing Network*) [33]. In this case, HyperNEAT evolves the connection weights and the connectivity between a fixed sensory input layer, hidden layer and motor output layer. HyperNEAT was selected since geometric features in the task environment, are exploited during controller evolution. In the collective construction task, such geometric feature include the relative positions of other robots, blocks, and the direction robots and blocks are facing. HyperNEAT has also been demonstrated as being capable of exploiting regularity and modularity in multi-agent tasks in order to evolve solutions that could not otherwise be evolved [21]. In the collective construction task, HyperNEAT is potentially beneficial, given that structures to be built are modular (comprised of a set of blocks), and regular (the same sequence of blocks can be repeated).

A. Robot Controller

All robots in a team used the same ANN controller, where each controller had N sensory input nodes (determined by a given experiment set), that adaptively mapped sensory inputs, via a hidden layer, to two motor outputs (figure 3) using HyperNEAT [19].

Figure 3 illustrates an example ANN configuration for N = 6. The ANN uses a 3 dimensional coordinate system for processing x, y, z positions in the CPPN in order to generate weight and bias values and connectivity. The CPPN indirect encoding of HyperNEAT allows evolved controllers to exploit the geometry of the task and the environment.

Also, HyperNEAT exploits the configuration of nodes in the ANN controller, thus the sensory input and motor output nodes must be in an appropriate configuration reflecting their position as part of a robot's morphology. Nodes for processing sensory inputs correspond to the direction each sensor faces. Thus, the input layer of the ANN controller is a circle of N evenly distributed nodes. Each node is a sensor, where the sensory *Field of View* (FOV) of all sensors forms a complete 360 degree FOV (figure 2). The rotation output node is in the center to preserve the angle between sensory input nodes. The speed output node is offset in the direction the robot is facing to signify forward movement at a given speed. The intermediate hidden layer reflects the configuration of the input layer, in order to preserve the geometry of the sensory input layer, that is the direction of each sensor's FOV (figure 3). The ANN is initialized with full connectivity between adjacent layers, however, partial connectivity can be evolved via the CPPN generating a zero weight. During the neuro-evolution process, the CPPN is developed via having nodes and connections added and removed, as well as connection weight values mutated [19]. Neuro-evolution parameters used in this study are given in table II.

1) Block Detection Sensors: Each robot has N *block detection* sensors each with a range of r (portion of the environment's length). Given that N and r are the subject of the experimental comparisons of this research, they are determined by the experimenter (section III). Robots are unable to detect each other, thus all cooperative interactions are *stigmergic* [34], taking place via the blocks and the built structure in the environment. A robot's 360 degree sensory FOV is split into N sensor quadrants (figure 2). Block detection sensors are constantly active for the duration of a robot's lifetime. Sensor q returns either 0 (no blocks detected) or 1 (one or more blocks detected) in sensor quadrant q. All detection sensor values are normalized within the range [0.0, 1.0].

2) Movement Actuators: Two motor outputs control a robot's heading and speed (R and S in figure 3) of movement. Motor output values are normalized within the range [-1.0, 1.0], where R, S = 0.0 corresponds to a default heading and being stationary, for the rotation and speed motors, respectively. Negative values of R and S correspond to anti-clockwise rotation and decreasing speed, where as, positive values correspond to clockwise rotation and increasing speed. R values of -1.0 and 1.0 equate to keeping the same heading, and an S value of 1.0 equates to the maximum distance a robot can traverse in one simulation iteration ($MaxDistance$ in table I).

III. EXPERIMENTS

Experiments test n robots in a bounded two dimensional continuous environment (100 x 100 units) containing a random distribution of type A and B blocks (table I). Robots are randomly initialized at the center of the environment. Figure 1 illustrates an example environment, containing 30 robots and 10 *type A* and B blocks. How different block types are connected is dictated by a *construction schema* defining the sequence of block types that must be connected together in order for a structure to be built. However, since this is a preliminary study to demonstrate a simple collective construction task, blocks can be connected in any sequence.

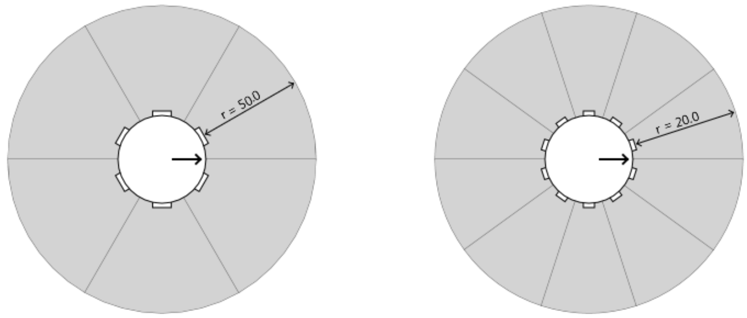

Fig. 2. Example robot sensory configurations (Left: 8 sensors, Right: 10 sensors). The sensory slices of N sensors comprise a 360 degree sensory field of view.

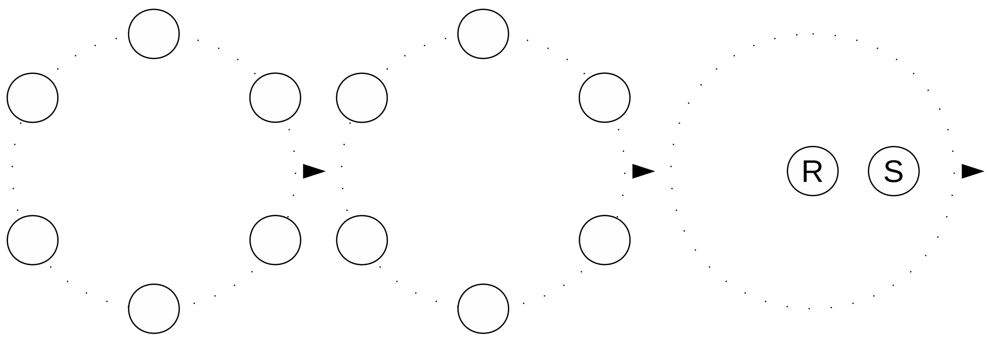

Fig. 3. ANN Topology as it relates to robot morphology: Sensory input layer (left), hidden layer (center) and motor output layer (right). Output nodes *R* and *S* determine a robot's rotation and speed, respectively. Arrows indicate the direction the agent is facing.

TABLE I. EXPERIMENT PARAMETERS

Generations	250
Sensors per robot	3, 6, 10
Sensor ranges	20, 50
Evaluations per genotype	3
Experiment runs	30
Environment length, width	100
MaxDistance	1
Team size	30
Team Lifetime (Task scenario length)	120
Lifetimes per generation	3
Type A blocks (1 robot to push)	10
Type B blocks (2 robots to push)	10

TABLE II. NEURO-EVOLUTION PARAMETERS

Mutation rate	Add neuron	0.25
	Add connection	0.8
	Remove connection	0.02
	Weight	0.1
Population size		100
Survival rate		0.3
Crossover proportion		0.4
Elitism proportion		0.1
CPPN topology		Feed-forward
CPPN inputs		Position, delta, angle

The difficulty of the construction task is regulated via requiring varying degrees of cooperation to make specific block connections. In this task, cooperation refers to at least two robots simultaneously gripping and pushing a block to touch another block, to which it automatically connects. One robot only is required to push type *A* blocks and two robots are needed to push type *B* blocks.

A. Experiment Design

Experiments measure the impact of varying robot morphology upon the evolved group behavior of a homogenous robot team given a collective construction task and a simulation environment. The collective construction task requires robots to search the environment for blocks and then push the blocks connecting them to others in the environment, in order to build a structure. Team task performance equals the number of blocks connected together during a team's lifetime (equation 1). An environment is defined as a distribution of block types, robots, and a construction schema.

The research objective was to efficiently ascertain an appropriate sensory morphology (number of sensors and range), such that a homogenous team maximizes its task performance.

Exploratory experiments of 12 different sensor morphologies were run to guide experiment design. These preliminary tests indicated that experiments testing a set of 6 sensory morphologies would be sufficient to satisfy the research objective. That is, a set of three sensor counts (3, 6, 10) and two different sensor ranges (20, 50) for each robot.

Each of six experiments tested one combination of the number and range of sensors for a fixed team size of 30 robots. Each experiment applied HyperNEAT to evolve team behavior for 250 generations. Initially, 500 generations were tested, but 250 was found to be sufficient to observe the convergence of team behavior for all morphologies tested. A generation comprised 3 *team lifetimes* (simulation task scenarios). One team lifetime was 120 simulation iterations, representing a task scenario that tested different robot starting positions, orientations, and block locations in an environment. For a given morphology, the task performance (fitness) of teams

TABLE III. TWO-WAY ANOVA INVESTIGATING THE IMPACT OF NUMBER OF SENSORS AND SENSOR RANGE ON TEAM TASK PERFORMANCE.

	Df	Sum Sq	Mean Sq	F-value	p-value
Range	1	0.0005	0.00050	0.261	0.610
Sensors	2	0.1210	0.06049	31.737	1.78×10^{-12}
Range:sensors	2	0.0041	0.00204	1.070	0.345
Residuals	174	0.3316	0.00191		

is an average calculated over 30 simulation runs, where the maximum team task performance is selected from each run. Experiment and neuro-evolution parameters are given in tables I and II, respectively. In table II, the CPPN inputs which affected the weight or bias of a given node were the *x*, *y*, *z* position of connecting nodes, the difference between their positions (*delta*), and the angle between them. These parameter values were determined experimentally. Minor value changes produced similar results for all morphologies. Except those parameters given in table II, other neuro-evolution parameters were set to values previously used for HyperNEAT [21].

The fitness function (equation 1) used in team (controller) evaluation was a weighted sum that included, the number of times a robot successfully found blocks (a in equation 1), the number of times *type A* blocks were pushed by *one robot* and connected with a built structure, and the number of times *type B* blocks were pushed by *two robots* and connected with a built structure (b in equation 1).

Parameter tuning experiments found that setting the weights (reward values r_a and r_b in equation 1) both to 1.0 resulted in functional controller evolution. Fitness was normalized to the range $[0.0, 1.0]$ using the number of blocks and agents required to move a given block i (s_i).

$$f = \frac{r_a a + r_b b}{r_b n + r_a \sum_{i=1}^{n} s_i} \tag{1}$$

IV. RESULTS & DISCUSSION

For a given experiment, the highest team task performance (fitness) achieved during an evolutionary run was recorded. An average of these maximum fitness values was then calculated over the 30 runs performed for each experiment. Figure 4 presents the average fitness achieved, by teams using each of the six team morphologies (section III-A) in terms of box plots. Figure 4 also illustrates fitness means, variances and outliers.

Figure 4 indicates that teams using only three sensors yield a significantly higher task performance, compared to the other morphologies tested. This difference was found to be statistically significant using a two-way analysis of variance (ANOVA) [35] (factors were *sensor range* and *sensor count*). ANOVA confirmed that the number of sensors has a significant impact on maximum fitness ($F = 31.737$, $p = 1.78 \times 10^{-12}$). However, the impact of sensor range was not found to be significant ($F = 0.261$, $p = 0.610$), and no interaction effect was found ($F = 1.070$, $p = 0.345$). The results of these statistical tests are summarized in table III.

This result implies that for homogenous teams that must accomplish a collective behavior task, then simpler morphologies (in this case, sensory configurations), leads to significantly higher team task performance. This is theorized to be the result of the demonstrated benefits of HyperNEAT applied to controller evolution, such as its capability to exploit modularity and geometric regularities in the task environment [21], [19], coupled with the lower dimensionality of the search space for ANNs with only three sensory nodes. Thus, in this case, the modular and regular nature of the task, requiring blocks to be connected together in a repeated fashion and the lower dimension search space facilitated a rapid convergence upon an effective collective behavior solution by HyperNEAT.

However, attaining these results depended upon morphological design choices by the experimenter. A robot's sensory configuration, that is, the input neurons of the ANN, were set relative to a robot's rotation, rather than being absolute in the environment. This design decision had two main motivations. First, it allowed evolved behaviours to be more robust in that it assumed the robot has no information about it's orientation with respect to global markers in the environment. Second, a robot's heading is not aligned with a specific sensor, rather it was exactly between two sensory FOVs (figure 2). This allowed a robot to more accurately move towards blocks with a feedback-control loop of minor adjustments to rotation. This effectively resulted in quick direct movement towards detected blocks, thus reducing the time needed to move detected blocks, and increasing average team task performance.

Also, the geometric relationship between the sensory inputs and the rotation and speed motors (figure 3), benefited from relatively few sensors, given that less sensory information had to be processed by the ANN. This relationship could be most effectively exploited by HyperNEAT for low dimensional search spaces, that is, a low number of sensors.

Figure 5 presents the progression of maximum team fitness over the course of controller evolution, averaged over 30 runs. Whilst figure 4 indicated that teams using three sensors achieved the highest overall fitness, figure 5 indicates that team fitness, for this lower number of sensors, after a steep increase during the first 50 generations, remains relatively constant throughput the rest of the evolutionary run. This implies that if controller evolution can only be run for relatively few generations, then selecting an appropriate sensory configuration yields significantly beneficial task performance advantages.

These results are supported by related research [36] that similarly demonstrates a minimal number of sensors and an appropriate sensory configuration leads to desired task performance, and increasing the complexity of the sensory configuration does not necessarily result in increased task performance.

This study's research objective was to find a minimal morphology (sensory configuration) such that a morphologically and behaviorally homogenous team evolve effective collective construction behaviors. The results are relevant to the larger fields of ER [2] and swarm robotics [18] that aim to minimize cost, weight and power requirements of robots. Another goal of these research fields is to synthesize problem solving collective behaviors that can be efficiently evolved either *a priori* in simulation and then transferred to counterpart physical robots

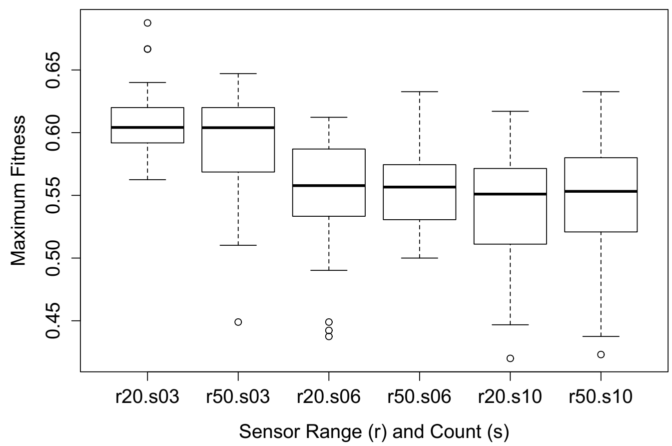

Fig. 4. Average maximum fitness yielded for each sensory configuration (experiment), after 250 generations of controller evolution. Averages are calculated over 30 runs for each experiment.

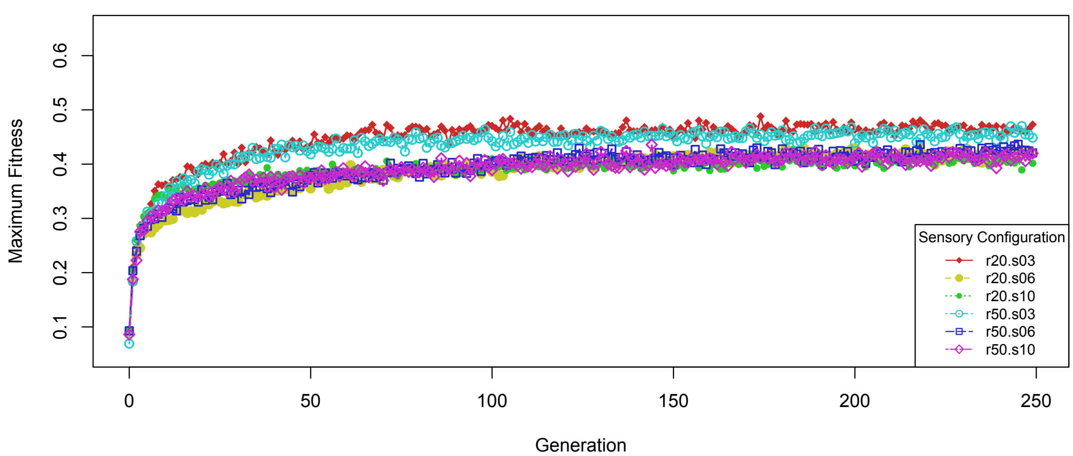

Fig. 5. Progression of best team task performance over the course of controller evolution, averaged over 30 runs. Red and blue curves at the top correspond to teams using three sensors, and yield a higher average task performance (with statistical significance), compared to the other sensory configurations tested.

[37], [38], [39] or evolved in real time as the robots interact with their environment [40], [41]. This research aims to address future applications of the former approach.

This study deviated from related research that co-evolves both morphology and behavior. Such approaches let a given artificial evolution process search a space of defined behaviors and morphologies in order to derive a sensory-motor configuration and coupled controller that is suited to solving a given task in a given environment [7], [42], [43], [8], [9], [44], [10], [45], [13], [46], [47], [48], [14], [15].

In this study the goal was for the experimenter to design and test a range of morphologies and then have a neuro-evolution process evolve an appropriate ANN controller. The motivation for this approach was the desire to find a minimal sensory configuration such that solutions to a collective behavior task are efficiently evolved. This falls in line with ER and swarm robotic research objectives of designing swarm robotic systems able to accomplish collective behavior tasks with minimal cost, weight (number sensors) and power requirements, where the problem solving collective behaviors of such robotic systems can be efficiently evolved in minimal time.

In related research that co-evolves behavior and morphology, especially that dealing with robot teams, there is a significant computational and time expense involved. That is, invariably large behavioral and morphological spaces must be searched and a huge number of possible behavior-morphology interactions that must be tested and evaluated. This research demonstrated that in collective behavior tasks where experimenters have some *a priori* knowledge from previous experiments [49] to guide morphological design, then a limited set of exploratory experiments that test a range of morphologies is sufficient (section III-A). Furthermore, methods that co-evolve behavior and morphology must often place significant constraints on the types of behaviors and morphologies that can be evolved in order to reduce the size of the search spaces and the number of behavior-morphology combinations that must be tested and evaluated. In such a case, morphological design by the experimenter, and then evolving controllers for these morphologies, is often just as effective as the behavior-morphology co-evolution approaches.

In this research the collective construction task was more akin to widely studied collective gathering tasks [24] that require agents (robots) to search an environment for resources, and then transport these gathered resources to a home area. In this case there was no specific home area, rather the first gathered block could be connected to any other, and then this initial structure became the focal point where all gathered blocks were transported to. Also, the task was made more complex via requiring cooperation (two robots) to move half of the blocks. Thus cooperative behavior and division of labor was mandated for the team to achieve optimal task performance. That is, if all blocks were to be gathered, teams had to effectively split into those that gathered *type A* blocks (one robot only) and those that gathered *type B* blocks (two robots needed). Experimental results achieved on average a maximum of approximately 60 percent of optimal team task performance (figure 4). This was a result of limiting the team lifetime duration (table I) to lower computational expense, and the lack of sensors to detect fellow robots. Both were in the interest of satisfying the research objective, and having purely stigmergic interactions between robots [34].

The inclusion of sensors for discriminating between team mates and resources in the environment has been demonstrated as beneficial in collective gathering and construction tasks [49] and will thus potentially form a part of future work that aims to test the impact of various morphologies (sensory configurations) as collective behavior task complexity increases. Specifically, future work will focus on testing a range of morphologically and behaviorally homogenous and heterogenous teams for varying degrees of complexity of a collective gathering and construction task. Increasing complexity in such a task entails having more block types, where each type requires a different degree of cooperation between robots to move, as well as testing a range of construction schemas. Construction schemas dictate the sequence and number of each block type that must be connected together in order for a structure to be built. Task difficulty can be regulated via the construction schema requiring that relatively scare block types be the first building blocks used in construction [49].

V. Conclusions

This research presented a study on the impact of different robot sensory configurations (morphologies) on evolving team behaviors in a robot team that had to accomplish a collective construction task. The collective construction task required cooperation in order for the team to optimally accomplish it. The team was behaviorally and morphological homogenous where the morphology was determined *a priori* by the experimenter and an accompanying ANN controller was evolved. The research objective was to investigate what degree of morphological complexity would be amenable to the efficient evolution of effective collective behaviors. This objective addresses future ER goals of designing robot swarms that have minimal cost, power and weight requirements, where problem solving collective behaviors must be efficiently evolved. Results indicate that minimal sensory configurations yield the highest task performance, and that effective collective behaviors can be more efficiently evolved for such minimal morphologies. In this collective construction task, increasing morphological complexity did not result in increased task performance over minimal morphology-behavior couplings.

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