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The Evolution of Robot Swarm Capable of Transporting Complex Shape

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Abstract

This paper presents a set of investigations achieved through a simulation involving a swarm of six robots transporting heavy objects of complex shapes that require the cooperative efforts of all six robots. This study focuses on the complexity of the objects' shapes, starting from a basic shape (i.e., Cuboid) to more complex shapes built from multiple basic shapes (i.e., Star and H-shape). The controller of the robots is a continuous-time recurrent neural network synthesized using artificial evolutionary techniques. The results indicate that evolution could find solutions for each object separately. However, a single generalized neuro-controller could not be obtained. This work unveils an interesting relationship between design choices and the complexity of object shapes. We analyze the effectiveness of cooperative transport strategies in terms of two metrics: the time required to sustain the transport and the quality of transport trajectories (i.e., sinuosity metrics).

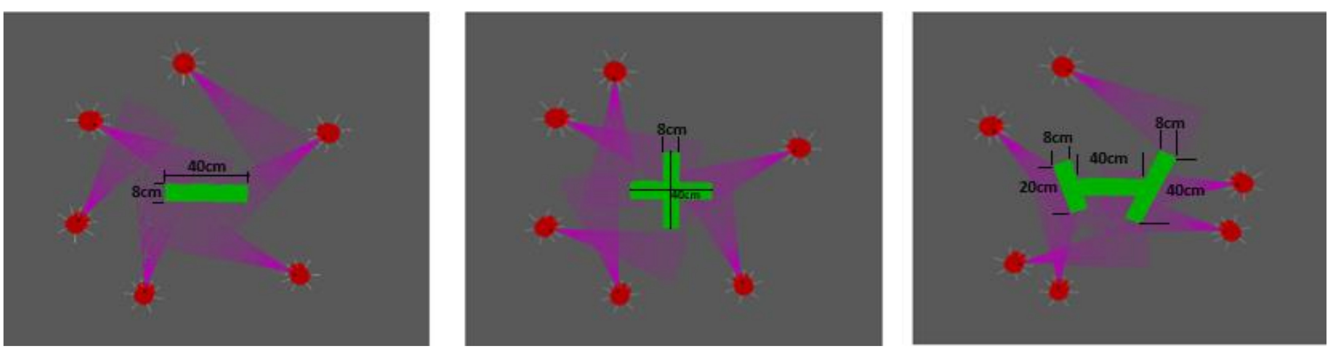
Keywords: Evolutionary robotics, Cooperative transport, Swarm robots, Complex objects.

1. Introduction

Collective transport, or cooperative transport, involves a team of robots working together to convey objects too heavy or oversized for a single robot to handle. A cooperative transport task requires complex coordination of the robot's forces to move the object. To successfully transport the object, the group must coordinate and synchronize their applied forces to initiate and sustain the object's movement in a common transport direction. Given its importance, cooperative transport by multiple robots holds great potential for applications ranging from construction and manufacturing to waste retrieval, search and rescue, and even invasive surgeries, tissue engineering, and biomedical applications at nanoscales [1, 2, 3, 4]. The research community has explored various aspects of cooperative transport, examining different transport strategies for pushing [5], pulling [6], grasping and lifting [7, 8], and different communication approaches, including centralized [9, 10], decentralized [11, 12] (also refer as distributed) and leader-follower approached [13]. This study concentrates on cooperative transport involving the transportation of complex-shaped objects. For a detailed review of cooperative transport in multi-robotic systems, we refer the reader to [14].

Another approach to designing cooperative transport in multi-robotic systems focuses on the development of control mechanisms based on the force model of robot-object interactions [6, 15]. Such strategies require a priori knowledge of the object's mass and shape. Conversely, other approaches focus on developing effective strategies that are agnostic to the object's configurations [16]. The majority of research work in cooperative transport has studied the transportation of basic shapes (e.g., cuboid, cylinder). Very limited research has studied strategies for transporting complex shapes. For instance, the research work in [17] proposes a decentralized approach for transporting complex objects. The study focuses on coordinating the direction of movements for robots that are placed in rings physically linked to the object. The results indicate that coordination of efforts can be achieved for objects of complex shape without the need for explicit communication between the robots. However, the results do not reveal whether the object's shape affects the coordination of the transport strategy since the robot-object interaction was constrained by the rings in which the robots were placed. Generally speaking, the process of cooperative transport involving complex shapes is not well understood. The strategies for reaching consensus or gathering quorum data on the direction of movement during the cooperative transport of objects with complex shapes remain ambiguous. Indeed, empirical data is scarce to explain the mechanisms that establish this vital cooperative activity. Therefore, it is imperative to propose diverse beliefs involving the mechanisms for aligning and coordinating forces for transporting objects of complex shapes.

This study examines what robots can collectively accomplish when engaged in the cooperative transport of complex objects. Specifically, we explore the development of strategies for a group of robots engaged in the collective transfer of complex-shaped objects constructed from basic shapes. The methodological approach employed in this study introduces a gradual increase in the shape complexity of the objects, starting from simple to more complex shapes. To achieve this objective, we designed three objects differing in shape. We began with a simple object of Cuboid shape refer to Fig.(1a), followed by an object with a relatively more complex shape called the Star object. The Star object consists of two Cuboid objects linked at the centre at a 90° angle see Fig. (1b). The complexity increases further for the third object, in which three cuboid objects are linked together such that short and long Cuboid objects are attached at both ends of an axial Cuboid object. The shorter object is linked at 120° and the longer object at 45° refer to Fig.(1c). We refer to this object as the H-shape object. We would like to bring to the reader's attention that this study is an extension of a previous study [18], in which we developed an effective transport strategy for a swarm robotics system transporting a Cuboid object tested on a group of six physical e-puck robots.



(a) (b) (c)

Figure 1. (a) The simulation environment for Cuboid object. (b) The simulation environment for Star object. (c) The simulation environment for H-shape object.

In this study, we aim to investigate the possibility of developing more effective transport strategies capable of transporting complex objects (i.e., Star and H-shape) derived from the object used in [18] (i.e., Cuboid). In this study, the neuro-controller used by the robot swarm is synthesized using an artificial evolution process. The results indicate that artificial evolution can find solutions that effectively transport either Cuboid, Star, or H-shape objects. However, generalized solutions could not be obtained. In other words, the evolution cannot produce a single neuro-controller strategy that transports all three objects without degradation in performance. A series of experiments have been carried out to analyze the best solutions for transporting the three objects using two metrics: the time required to sustain the transport to the end of the trial and the quality of the transport strategy in terms of the sinuosity metric.

2. Methods

In this study, a neuro-controller is synthesized using an evolutionary process to generate an effective cooperative transport strategy for a swarm of homogeneous robots (i.e., the neuro-controller is replicated across all robots in a homogeneous robotic swarm) to transport objects of complex shapes. The task involves moving objects shaped like cuboids, stars, and H-shapes (see Figure 1) at least 1 meter from their initial positions. The selection of these particular object shapes is intentionally designed to progressively increase the complexity of the transport strategies needed, ranging from the Cuboid to the H-shape objects. The aim is to explore how effectively the evolutionary process can develop solutions for the challenges presented by the diverse shapes of these objects.

2.1 Task and Simulation Model

The task required a swarm of six robots to transfer heavy objects with complex shapes at least 1 meter from their starting positions. The mass of the object is set to 600 grams to ensure that it cannot be transported without the collective efforts of all six robots. Initially, the robots are positioned in a limitless hall with a flat landscape, arranged in an imaginary circle with the object at the circle's centre (see Figure 1). The distance between each robot's centre and the object's centre is set at 50 cm. This initial setup ensures that the robots approach the object from different directions, necessitating complex coordination of their push forces to settle on a shared transport direction.

The simulated robot models the physical e-puck robot [19], a popular platform often used in swarm robotics experiments. It is equipped with 8 Infrared proximity sensors IR_i, with i = 0, 1, ..., 7 (indicated by the small eight white rays around each robot in Figure 1). The camera's visual range is limited to 50 cm and is modeled in the simulation such that the field of view is divided into three sectors C_i, with i = 1, 2, 3 (indicated by the pink rays for each robot in Figure 1). Each sector provides four distinct values:

0 if nothing is within the sector domain of view, 0.4 if it detects red colour (i.e., another robot), 0.7 for green colour (i.e., the object), and 1.0 if both red and green colours are seen simultaneously. The robot is also equipped with an optic-flow sensor and an optical camera mounted under the robot's platform, providing 2D displacement information along the X-axis (i.e., $[-X, +X]$) and Y-axis (i.e., $[-Y, +Y]$). This optic-flow sensor provides important feedback on the consequences of its movement. This sensor is specifically designed and built for this cooperative transport task (see [18]).

Our simulation employs a Bullet physics engine, a robust tool that offers a realistic simulation of force dynamics, including torques, frictions, and collision responses. Additionally, the robots' sensors and actuators, as well as the initial positions and orientations of the robots, are incorporated with noise that varies in each trial. Each evolutionary run is associated with a different seed number fed into the random number generator, affecting not only the noise in the simulation but also the random initial parameters for the evolved neuro-controllers. Our simulation has proven its ability to bridge the reality gap, ensuring that the evolved controller can be transferred to the physical e-puck robot without any drop in performance (see out experiments with physical robots in [20].

2.2 The Controller and the Evolutionary Algorithm

Fig .(2)shows the structure of the continuous-time recurrent neural network (CTRNN) that controls the robot. This network comprises 15 input neurons corresponding to the values from 15 sensors (8 IRs, 3 camera sectors, and 4 values for the optic flow sensors), 6 hidden neurons, and 4 output neurons. These output neurons are responsible for controlling the left and right wheels of the robot. Figure 2 shows the efferent connections for a single neuron in each layer. Each hidden neuron is connected afferently to every neuron in the input layer and to each other hidden neuron, ensuring a self-connection. In a similar manner, every output neuron is connected afferently to all hidden neurons. The parameters of the CTRNN are synthesized using a simple genetic algorithm featuring tournament-based selection. The population consists of 100 individuals. The top 10 individuals with the highest scores (i.e., the elites) are carried over to the new generation unchanged. The next 60 individuals undergo mutation (with a probability of 0.04) and recombination (with a probability of 0.3). The remaining 40 low-scoring individuals are disregarded. In [18], a detailed illustration of the controller and the evolutionary algorithm can be found.

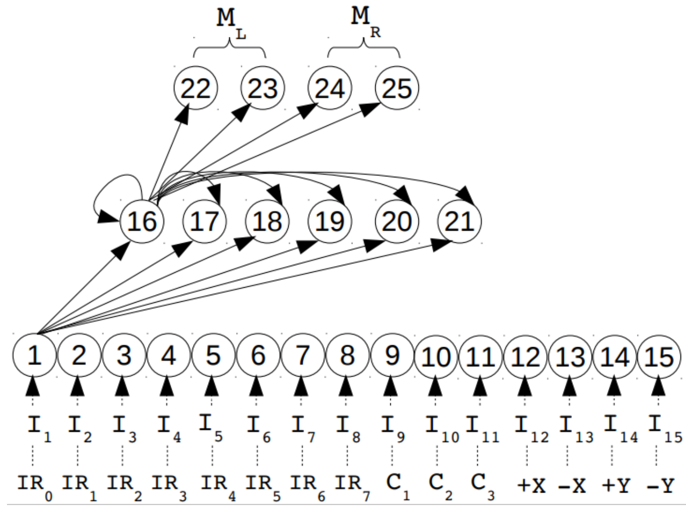


Figure 2. The Continuous-time recurrent neural network that controls the robot. For clarity purpose, the figure shows the efferent connections for a single neuron in each layer. Every hidden neuron is connected afferently to each neuron in the input layer as well as to every other hidden neuron, including a self-connection. Similarly, each output neuron is linked afferently to all hidden neurons. Below the input layer, the connection between sensory neurons and sensors is detailed.

During the evolution, all groups are evaluated nine times $E = 9$. Three evaluations for each object's shape (f_{cuboid}, f_{star}, $f_{H-shape}$). Each trial lasts for 600 simulation steps (1 second = 0.01 simulation steps). At the start of every trial, the six robots are positioned 50 cm away from the object, with random positions and orientations, to ensure that the evolved neuro-controller is robust to variations in initial positions and orientations. In every trial (e), the fitness function (f) rewards groups that move closer to the object and transport it as far as possible from its initial position (refer to equation 1). The genotype fitness score (F) is computed as follows:

$$f_{cuboid}, f_{star}, f_{H-shape} = \sum_{r=1}^{R}(1 - d_r) + D_{obj}; \qquad with\ R = 6; \tag{1}$$

$$F_e = f_{cuboid} + f_{star} + f_{H-shape} \tag{2}$$

$$F = \frac{1}{E}\sum_{e=1}^{E} F_e; \qquad with\ E = 9; \tag{3}$$

With f_{cuboid}, f_{star} , $f_{H-shape}$ is the fitness for Cuboid, Star, and H-shape objects, respectively. d_r is the distance between the robot r and the object at the end of the trial time. D_{obj} is the distance between the object's place at the start and end of the test. The average fitness score F for the genotype for the nine evaluations $E = 9$ is computed using equation 3. Regarding computational complexity, the time required to complete a single evolutionary run, when executed on a Dell PowerEdge server equipped with 64 cores and 256 GB of main memory, is approximately 10 hours.

3. Results

The preliminary objective of this study is to develop a control system for a homogeneous swarm of robots to transport heavy objects with complex shapes. The goal is to generate solutions that can adapt to the challenges involved in the group coordination process for Star and H-shape objects, yet the performance should not degrade for cuboid objects. To achieve this objective, we conducted five different evolutionary simulations. Each simulation lasted for 2000 generations, following the methodological setup described in Section 2. In order to select the best genotype in every evolutionary simulation (i.e., neuro-controller), we re-evaluated all genotypes from generation 1000 to 2000. Each genotype underwent a total of 240 trials (i.e., evaluations). For each object, 80 trials were conducted. In every trial, the starting position and orientation of the six robots varied. To ensure the requirement of collective transport, the mass of the three objects was set to 600 g, making it impossible to transport them without the collaborative effort of all six robots.

In every trial of the re-evaluation test, the object was positioned in the center of an endless flat hall, and the six robots were placed 50 cm from the object, with random positions and orientations. The requirement of a 50 cm initial distance between the robots and the object was necessary to ensure that each robot could initially see the object, as it was within its camera range. Otherwise, the robots would need to develop an exploration strategy to locate the object, which is not within the scope of this research. Each trial could last for a maximum time of 180 seconds, and the trial could end earlier if the swarm managed to transfer the object at least one meter from its starting place. Transporting the object, a distance of one meter, was a condition for considering the trial successful.

Fig. (3) reveals different performance trends for the best group in each run. For example, the best group from run H displays the best performance with the H-shape object, but its performance significantly degrades with the Cube and Star objects. Similarly, the best group from run S shows the best performance with the Star object, yet its performance degrades with the Cube and H-shape objects. For the best groups from runs X, C, and M, a similar trend is observed, with good performance in the Cuboid object but a drop in performance with the Star and H-shaped objects. It can be concluded that the three objects require different group coordination skills. In other words, the evolutionary process can synthesize neuro-controllers with specialized skills for transporting Cuboid, Star, or H-shape objects. However, it struggles to generate a single neuro-controller with effective transport strategies that can handle all three objects

without a drop in performance.

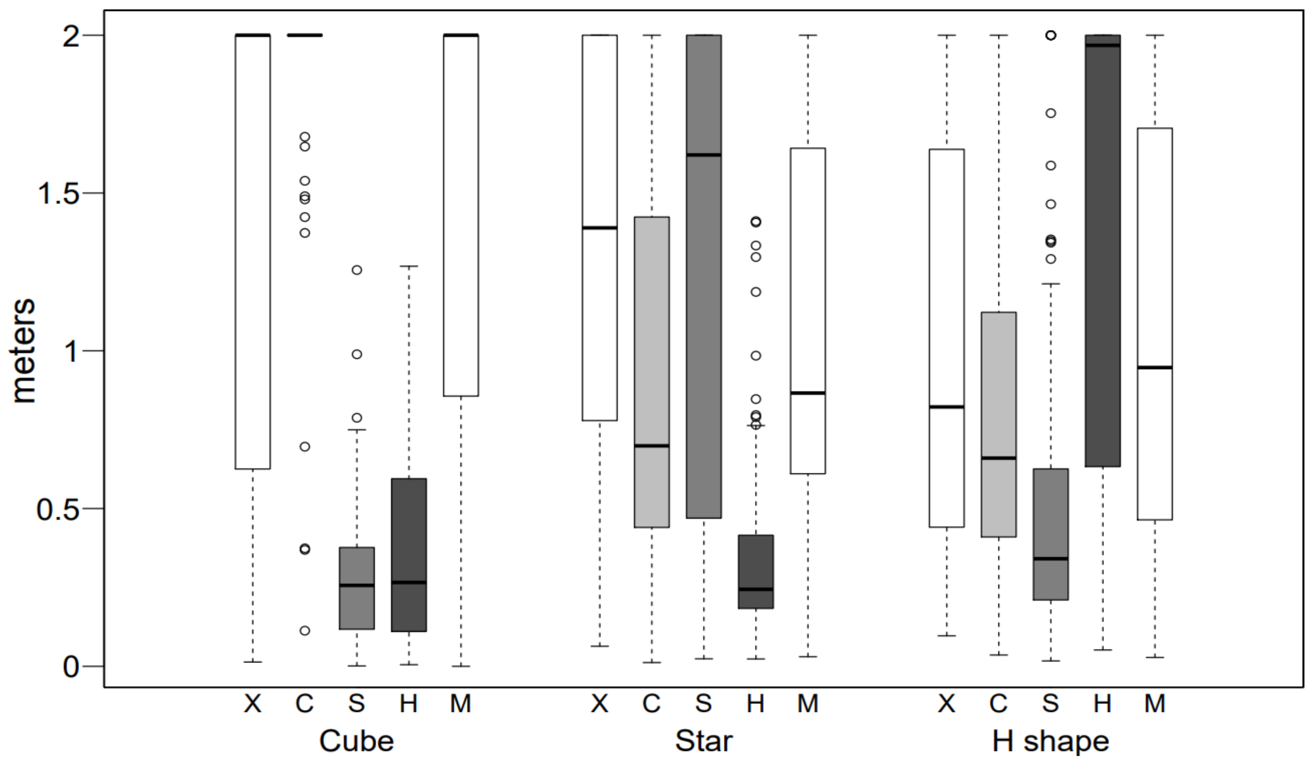


Figure 3. Box plot showing performance of the best group across five runs (i.e., X, C, S, H, and M) for the three types of object shape (i.e., Cube, Star, and H-shape). The y-axis indicates

the distance in meters the object has been moved in each trial. Each box plot comprises 100 trails in which the groups attempt to transfer the object from beginning place up to

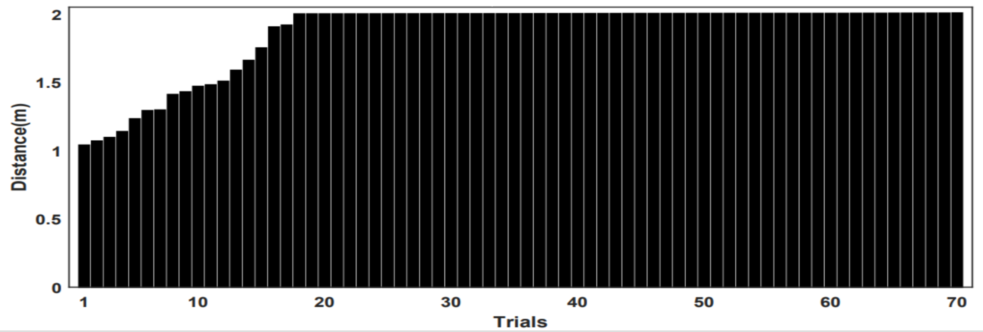
Despite this limitation, it is interesting how the evolutionary process finds solutions for the Star or H-shape objects, which require complex coordination of actions to synthesize the push force of the robots to push the object. From the videos' observations of transporting the Star object (see [21]) and the H-shape object (see [22]) show that the robots adopt different strategies to coordinate their pushing forces, clustering around the object and varying the position and direction of the applied forces. Despite this complexity, evolution can synthesize a neuro-controller that specializes in transporting either one of the three objects effectively.

3.1 Further analysis of the best evolved groups

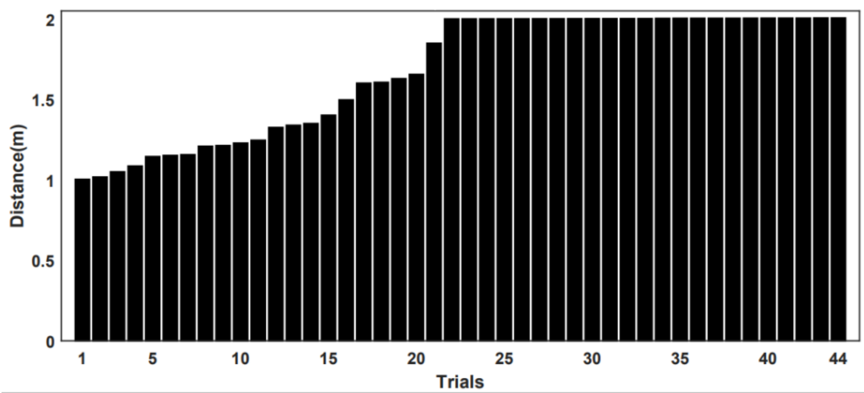
We choose the best group from run C for further analysis to better understand the performance of the evolved neuro-controller. The reason for choosing the genotype in the best group of run C is because it shows the highest accumulated success rate among all other groups. Fig. (4) displays the group C performance in a bar plot format for the Cuboid, Star, and H-shape objects. The x-axis indicates the number of successful trials out of the total 80 trials conducted for transporting each object. The y-axis shows the distance the object has been transported from its initial position to the final position at the end of the trial.

The Cuboid bar plot indicates 70 successful trials out of 80 trials. However, for the Star and H-shape objects, the performance degrades to 44 and 48 successful trials, respectively. This suggests that the group C neuro-controller is specialized in transporting the Cuboid object, yet it still exceeds the 50% threshold success rate for the Star and H-shape objects. It's worth mentioning that the poor performance in Star and H-shape does not necessarily mean that the robots were unable to move the object in the unsuccessful trials. In fact, in the majority of these unsuccessful trials, the group was able to coordinate and move the object but did not meet the 1-meter transport criterion. Indeed, the success criteria defined are quite stringent in terms of the mass chosen for the object and the distance transported.

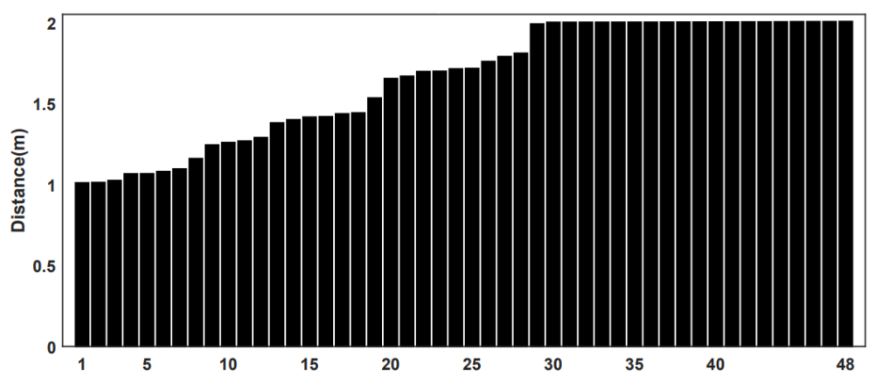
Fig. (5) presents a box plot of the time required to transport the object at the smallest 1 meter from its beginning position for the three types of objects. Recall that the maximum duration of the trial is set to 180 seconds. Observing the medians of the three boxes, it's evident that the robots require relatively less time for the Cuboid object compared to the H-shape and Star objects, where their medians are almost at the maximum trial time. This serves as further evidence that the H-shape and Star objects necessitate complex coordination efforts to align the pushing force of the robots for successful transportation. Moreover, the medians for the Star and H-shape objects hitting the maximum trial time indicate that the robots require more time for these types of objects to successfully transport them at least 1 meter distance. However, in this research, we adhere to the 180-second trial limit because we are interested in the development of efficient cooperative transport strategies that do not require significant time to generate coordinated action. Hence, this criterion is chosen.



(Cuboid)



(Star)



(H-Shape)

Figure 4. The bar plot shows the number of successful trials in which the robots transport the object at the smallest one meter from the beginning position for Cuboid, Star and H-shaped, respectively. The x-axis indicates the distance in meters of the object has been transported during the trial time, and the y-axis shows the number of successful trials (> 1.0 meter).

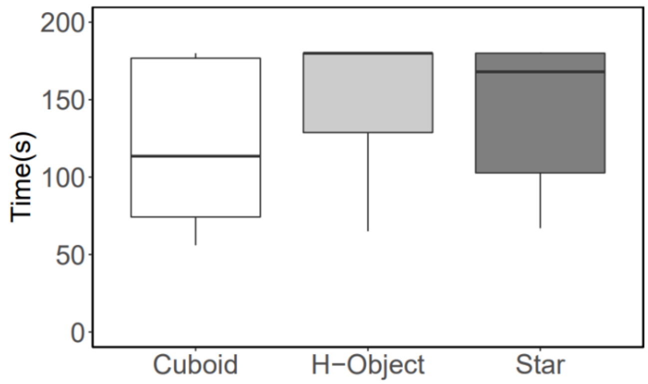


Figure 5: Box plot showing time required to accomplish the task successfully for the three types of object shape (i.e., Cube, Star, and H-shape). The y-axis indicates the time in seconds the object has been moved in each trial (remember the maximum trial time is 180 s). Each box plot comprises only the successful trails in which the groups transport the object at the smallest one meter from its beginning position.

A key metric used to measure the quality of the transport strategy is referred to as sinuosity. This metric was originally proposed in [23] to assess the efficiency of transport strategies in real ant species. Sinuosity (S) is defined as follows:

$$S = \frac{J_{obj}}{D_{obj}} \quad (4)$$

where D_{obj} corresponds to the object's displacement (i.e., the straight line distance from the object's start position to its final position), and J_{obj} is the actual trajectory length that the object follows during transport from the beginning to the end of the test. The J_{obj} and D_{obj} are calculated concerning the object's centre of mass. A higher sinuosity value indicates an inefficient transport trajectory, which is often due to poor coordination of the pushing force, causing the object to frequently change its direction of movement, resulting in a longer trajectory path. On the other hand, a lower sinuosity indicates efficient transport, where coordination of pushing forces is quickly established and maintained throughout the trial. The lowest possible sinuosity value is 1, indicating that

$J_{obj} = D_{obj}$

Fig. (6) presents a box plot for the sinuosity values of the successful trials. The white, light-grey, and dark-grey boxes correspond to the sinuosity values for the Cuboid, H-shape, and Star objects, respectively. It is evident from the white box that the trajectories for the Cuboid object are less sinuous (i.e., with a sinuosity median closer to 1) compared to those for the H-shape and Star objects. This finding is supported by visual observations of the robots' behaviour during the transport of the Cuboid object. These observations indicate that the robots quickly and efficiently coordinate their moving forces in a shared direction of transportation and maintain this coordination throughout the duration of the transport. Conversely, in the case of the H-shape and Star objects, the robots take a significant amount of time to change their point of applying force on the object in order to find a common direction of pushing. This behaviour results in two consequences: one is the increase in trial time, and the other is the frequent change in the object's direction of movement, which leads to a longer transport trajectory and ultimately a higher sinuosity.

The results of the time and sinuosity tests demonstrate a correlation between the duration of the trial and the sinuosity of the transport; both metrics decrease in efficient strategies, as observed in the transport of the Cuboid object, and increase in less effective strategies, such as those for the H-shape and Star objects. This suggests that a completely different set of skills is required for each type of object to be successfully transported. Despite these challenges, the evolutionary process is capable of finding a successful path to synthesize a neuro-controller with an efficient strategy for transporting either the Cuboid, Star, or H-shape objects see Fig. (3).

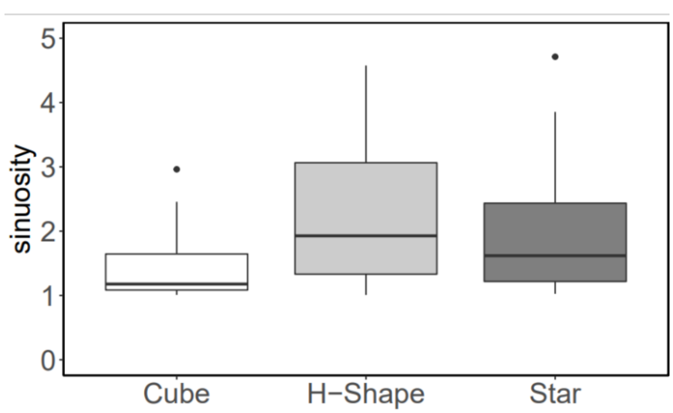


Figure 6. Box plot showing Sinuosity metric used to evaluate the effectiveness of the transport trajectories for the successful trials of the three types of object shape (i.e., Cube, Star, and H-shape). The y-axis indicates the Sinuosity value.

4. Conclusion

This research describes a list of experiments conducted in simulation. The task required a swarm of six robots to transport heavy objects of complex shapes, which necessitated the cooperative efforts of all the robots. In particular, three objects have been investigated, which vary in their shape complexity, starting from a basic shape (i.e., Cuboid) to more complex shapes built from multiple basic shapes (i.e., Star and H-shape). The robot's controller is a dynamic neural network (i.e., CTRNN) synthesized using artificial evolutionary techniques. We ran five different evolutions, each lasting for 2000 generations. The results indicate the best neuro-controllers in every run are specialized for transporting a single object effectively but not the others. These results indicate evolution can find solutions for the complexity of the object's shape, but it could not produce a single neuro-controller that generalizes to transport all three objects.

This study sheds light on an interesting relationship between design choices and the complexity of the shape of the object being transported. We analyze the effectiveness of the evolved group transport strategies of the best neuro-controllers using two metrics: the time required to sustain the transport to the end of the trial and the quality of the transport strategy in terms of sinuosity metric. The results indicate that time and sinuosity increase as the shape complexity of the objects increases. Generally speaking, the analysis of time and sinuosity, in addition to the visual observations of the robots' behaviours during transport, provides evidence that even a relative increase in shape complexity of the object requires the group to adopt different strategies in order to coordinate their pushing forces in a shared direction and maintain the transport for the entire time of the task. Consequently, the designer needs to adopt the design methodology considering the particular aspects of the shape complexity of the object.

This study suggests that there is a necessity for further investigation into the effect of the complexity of objects' shapes on the effectiveness of transport strategies. In the future, we will continue looking at the problem of designing a single neuro-controller that can effectively transport the three objects efficiently. One possibility to address this problem is to use multi-object optimization, a single objective for each object's shape. Another possibility is to use perceptual discrimination means to differentiate between the objects so that the group can switch between different neuro-controllers specialized for the detected object. Furthermore, we also plan to deploy the developed solutions to the physical e-puck robot.

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تطور سرب الروبوتات القادر على نقل الأشكال المعقدة

الخلاصة: *تصف هذه الورقة مجموعة من التجارب التي أجريت في مجال المحاكاة والتي تتضمن سربًا من ستة روبوتات تنقل أشياء ثقيلة ذات أشكال معقدة تتطلب جهودًا تعاونية من جميع الروبوتات الستة. تركز هذه الدراسة على مدى تعقيد أشكال الكائنات، بدءًا من الشكل الأساسي (أي المكعب) إلى الأشكال الأكثر تعقيدًا المبنية من أشكال أساسية متعددة (مثل الشكل النجمي والشكل H). وحدة التحكم في الروبوتات عبارة عن شبكة عصبية متكررة ومستمرة تم تصنيعها باستخدام تقنيات تطورية اصطناعية. تشير النتائج إلى أن التطور يمكنه إيجاد حلول لكل كائن على حدة. ومع ذلك، لا يمكن الحصول على وحدة تحكم عصبية معممة واحدة. يكشف هذا العمل عن علاقة مثيرة للاهتمام بين خيارات التصميم وتعقيد أشكال الكائنات. نحن نحلل فعالية استراتيجيات النقل التعاوني من حيث مقياسين: الوقت اللازم للحفاظ على النقل وجودة مسارات النقل (أي مقاييس الانحناء).*

الكلمات المفتاحية: الروبوتات التطورية، النقل التعاوني، الروبوتات السربية، الأشياء المعقدة.