Coevolving Behavior and Morphology of Simple Agents that Model Small-scale Robots

Milen Georgiev, Ivan Tanev and Katsunori Shimohara

Graduate School of Science and Engineering, Doshisha University

1-3 Tatara-Miyakodani, Kyotanabe, Kyoto 610-0321, Japan,

email: *shogo@shogo.eu, {itanev, kshimoha}@sil.doshisha.ac.jp*

ABSTRACT

Humanity have long strived to create microscopic machines for various purposes. Most prominent of them employ nano-robots for medical purposes and procedures, otherwise deemed hard or impossible to perform. However, the main advantage of this kind, of machines is also their main drawback – their small size. The miniature scale they work in, brings a lot of problems, such as not having enough space for the computational power needed for their operation, or the specifics of the laws of physic that govern their behavior. In our study we focus on the former challenge, by introducing a new standpoint to the well-studied predator-prey pursuit problem (PPPP) using an implementation of very simple predator agents, using nano-robots designed to be morphologically simple. They feature direct mapping of the (few) perceived environmental variables into corresponding pairs of rotational velocities of the wheels' motors. Our previous, unpublished work showed that the classic problem with agents that use straightforward sensor, do not yield favorable results as they solve only a few of the initial test situations. We implemented genetic algorithm to evolve such a mapping that results in an optimal successful behavioral of the team of predator agents. In addition, to cope with the previously described issue, we introduced a simple change to the agents in order to improve the generality of the evolved behavior for additional test situations. Our approach is to implement an angular offset to the visibility sensor beam relative to the longitudinal axis of the agents. We added the offset to the genetic algorithm in order to define the best possible value, that introduces most efficient and consistent solution results. The successfully evolved behavior can be used in nano-robots to deliver medicine, locate and destroy cancer cells, pinpoint microscopic imaging, etc. [1]

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CCS CONCEPTS

Computing methodologies → distributed artificial intelligence; robotics;

KEYWORDS

Predator-prey pursuit problem, multi-agent systems, genetic programming

1. INTRODUCTION

With advancement of technology and invention of the optical and electric microscopes, the humanity started exploring the miniature world. With these new discoveries, however, new problems started to arise. To discover the solutions to them, mankind turned to creating micro- and nanomachines on their own [15]. As a species, striving to survive the various lethal conditions, we are exposed to, the most prominent field of use for these new nanomachines is in medicine. There are many procedures that are hard to perform by a human medical doctor and for which the newly created micro-robots are perfectly suited [14]. Such tasks are brain surgeries, video diagnostics in hard to reach places and pin-point drug delivery, much needed in chemotherapy, where the medicine could also harm the body tissues. Some of the advantages that the nano-technology provides are minimal tissue trauma, relatively less recovery time, less post-treatment care required, continuous monitoring and rapid response to a sudden change in condition [18].

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In our research we are employing a Multi-Agent system (MAS) to create a controller which can be used in simple nano-robots. The advantage of the developed MAS, compared to centralized systems with analogical functionalities, is that it offers increased modularity, reduced complexity (offering an intuitive solution to the divide-and-conquer approach of developing and deploying complex software systems), and flexibility to a diverse software- and hardware platforms.

From consumer viewpoint, the benefits of using MAS are, its superior robustness, increased fault tolerance, scalability, and performance. The latter is especially true, as the MAS could solve (inherently parallel, or distributed) problems much faster than centralized (or single-agent-) systems. Moreover, due to their complex, non-linear nature, MAS could often solve problems that a single agent is unable to solve. The whole team of multiple agents is expected to show behavior that can be regarded as emergent (high-level) property of the much simpler (lower-level) properties of the agents, or as a whole that is "more than the sum of its entities" (Aristoteles, 384 a.C.- 322 a.C.), and, therefore, could not be devised by applying the conventional top-down software engineering approaches.

In our work we consider MAS applied for simulation of societies of mobile robots. The agents, are represented as autonomous software systems that are situated in simulated environment, have perception of the state of this environment, and act accordingly upon it, have a precise model for the functionality of the main components – sensors, controllers, and actuators – of real-world mobile robots. This work aims especially at the design features of small-scale robots – micro-, nano-, and DNA robots. Nevertheless, various challenges can be considered as currently slowing the progress of the real-world applicability of micro- and nano- robots. One of the greatest challenges, come from the very advantage of these robots – their small size. The physical constrains imply that these robots could not feature a complex morphology – both the sensors and moving mechanisms need to be very simple to be able to fit in the limited space of the agent's body. Other researchers have already found ways to create robots on a nano-scale, which are guided by an external force [16] [17]. Our work focuses on creating autonomous units which can traverse the human body without the need of outer force or a monitoring. The agents would be behaviorally simple too, in that their decision-making would involve a direct mapping of the (few) perceived environmental states into actuators commands, instead of featuring a complex decision making mechanism in each one of them. Most likely the communication (if any), between the individual agents, would be impossible to be realized in a direct manner and would be fulfilled implicitly, using the environment. Such robots can be regarded as an ultimate case of Occam's razor principle, applied both the morphology and decision-making of mobile robots.

To comply with this definition of simple robots, in our research we consider predator agents featuring a single beam (line-of-sight) sensor providing just two bits of information, and two wheels (arranged in a differential drive configuration), rotational velocities of which are controlled by two motors. Their purely reactive behavior is realized by a simple decision-making that does not require any computing. Instead, it involves a direct mapping of just four perceived environmental states into corresponding pairs of rotational velocities of wheels' motors.

Similar robots were previously modeled as agents by Gauci et al [1]. The agents were able to self-organize in order to solve the simple robot aggregation problem. The same framework was also successfully applied for the more-complex object-clustering problem [2] in which the agents need to interact with an additionally introduced immobile object. The very possibility of a team of such agents to conduct an elaborate social (surrounding) behavior in an environment featuring dynamic objects was recently demonstrated by Ozdemir et al [3] in solving the shepherding problem, where a team of simple agents (shepherds) need to guide multiple dynamic agents (sheep) toward an a priori defined goal.

In our study, we are proposing the use of similar team of simple agents in the solution of a different task – the well-studied, yet difficult to solve predator-prey pursuit problem (PPPP) [5] [6] [7] [8]. In the considered PPPP, eight identical, simple agents (predators) are required to capture the single dynamic agent (prey). Our *objective* is to investigate the possibility of applying genetic algorithms (GA) to evolve such (optimal) direct mapping of the four perceived environmental states into respective velocities of the wheels of predator agents, as well as sensory beam offset, that results in an optimal behavior of the team of agents, which will lead to capturing the prey.

Our motive for using an implementation of PPPP is due to the increased complexity of the problem, compared to the previously studied tasks. We desire to investigate whether the agents will be able to successfully complete the assignment. In comparison to the previously investigated domains, PPPP requires the agents to exhibit a more diverse behavioral set, including exploration of the environment, surrounding and capturing the prey. In contrast to [3], in our implementation of the PPPP framework, the emergence of such behaviors is made additionally complicated, by introduced constrains to the sensory and moving abilities of the predator agents. Modeling the real world, they feature myopic, limited-range (compared to the unlimited vision in other works) sensors, and their movement speed is equal to that of the prey, instead of being faster. Furthermore, the initial position of the predators is such that the prey is not being surrounded, which may ease the task of capturing it. This can be viewed as injecting the clustered team of robots at a certain point into the human body.

An additional motivation of our research is the recognition that while many real-world scenarios could be, indeed, reduced to the previously researched wall-following, dispersal [4], clustering [1], and shepherding problems [3], there would be few scenarios – requiring a direct physical contact with an active prey – that could be modelled by the so far unconsidered PPPP. These scenarios include pinpoint drug delivery, surrounding and destroying (cancer) cells or bacteria, gathering around cells to facilitate their repair or imaging, etc

The additional rationale to focus on this application domain is that, even if the previous implementations of PPPP do actually assume some form of *subjective* simplicity of the predators – such as lack of communication abilities, having sensors that perceive just one (the closest) entity in the world, and purely reactive architecture [9] – the agents are in no way *objectively* simple as a significant amount of computing is still required by their perception subsystems (e.g., in order to determine the closest entity from all entities in the omnidirectional field of view) and their decision-making. To the best of our knowledge, *objectively* simple predators have not been implemented in the so far investigated instances of PPPP.

2. THE ENTITIES

2.1 Predator Agents

Each of the eight (identical) predator agents model a simple cylindrical robot with a beam sensor featuring a limited range of visibility, and two wheels (controlled by two motors) in a differential drive configuration.

The beam sensor provides two bits of information, where each bit encodes whether an entity – either a (nearest) agent or the prey, respectively – is detected (if any) in the line of sight within the limited range of visibility. The implementation of such sensor in nano-robots would consist of two photodetectors sensitive to two different, non-overlapping wavelengths of (ultraviolet, visible, or infrared) light emitted by predators and prey, respectively. Each of these two photo-detectors provides one bit of information. For the considered cylindrical predator agents with two wheels in a differential drive configuration, this axis could be defined as the axis that is perpendicular to the axis of the wheels and crosses the geometrical center of agents. Equipped with such sensors, the predators could perceive only four possible states of the directly faced environment. The main features of the agents are shown in Table 1.

Table 1: Features of the entities

Feature	Predator	Prey
Number of agents	8	1
Diameter, µm	16	16
Length of the axis of wheels, µm	16	16
Max linear velocity of wheels, µm/s	10	10
Max speed of predator agents, µm/s	10	10
Type of sensor	Beam (line-of-sight)	Omnidirectional
Range of visibility of the sensor, µm	200	50
Orientation of sensor	Counter clockwise offset (2~40 degrees)	-

In our previous unreleased work, we noticed that the classical case, where the sensor is aligned with the longitude axis of the agents, the team struggles to find a solution for more than a few initial situations as seen in figure 1 below.

It should be noted, that the environmental states do not provide the predators any information regarding the distance to the perceived entity or the total number of entities in range of the sensor. The state <11>, as shown in Figure 2, is the most challenging one to perceive. It could be perceived, however, under the following assumptions: (i) the prey is taller than predators, (ii) in order not to obscure the shorter predators, the cross-section of the prey is either much narrower than predators, or (at least partially) transparent for the light emitted by predators, and (iii) a conic shape of the beam pattern of the (modeled as ideal, single line of sign) light sensors of predators.

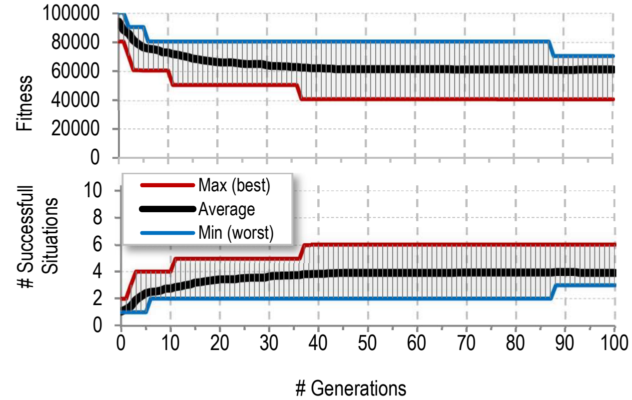

Figure 1: Convergence of the best fitness (top) and the number of successful situations (bottom) of 32 independent runs of GA. The envelop illustrates the minimum and maximum values in each generation.

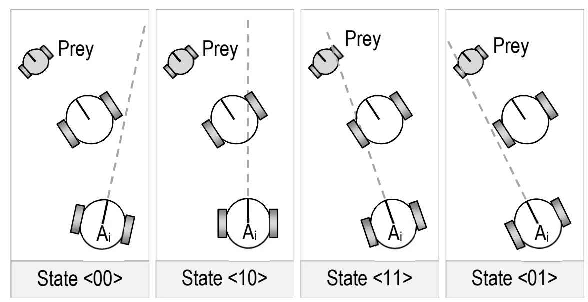

Figure 2 : The four possible environmental states that are perceived by any given predator agent

To counter the previously mentioned issue, we could widen the gap between the capabilities of both types of agents in PPPP – either by deteriorating the sensory or moving abilities of the prey or enhancing the abilities of the predator team, or combination of both. However, we do not wish to simplify the task placed on the predators, in such a way.

To address the challenge in evolving the general behavior of predators in the introduced instance of PPPP, we will focus on modifying the morphological features of the predators. Instead of the commonly considered straightforward sensor, we suggest placing a counter clockwise offset to the angle between the sensor and the longitude axis of the predator agents. Notice that an eventual angular offset of sensors will in no way compromise the intended simplicity of the agents. We are curious if such a change will improve the general performance of the evolution of the team, of predator agents and increase the robustness of the evolved behavior to new initial situations.

The proposed approach is inspired by the visual navigation of nocturnal insects, achieved by constantly maintaining the source of light (e.g. moon) within the sight of the facets of a compound eye. The sensors of the predators could be viewed as an analogy of a very simple, single-facet eye. From another point of view, we speculate that a sensory offset would allow the predators to implement an equiangular (proportional) pursuit of the prey, aiming at the (estimated) point of contact with the moving prey, rather than the currently perceived position of the latter.

The entirely reactive behavior of the predator agents could be described as a direct mapping of each of the perceived environmental states into a corresponding rotational speed of the wheels motors. For simplicity, instead of mapping into rotational speeds of motors, from hereon we will assume a mapping into *linear* velocities of the wheels, expressed as the percentage – within the range [-100 %…+100 %] – of their respective maximum linear velocities (10 μm/s, as shown in Table 1). For example, a velocity of -20 % implies that the motor of the wheel is rotating at 20 % of its maximum angular velocity (RPM), and the wheel propels the corresponding side of the robot in a backward (negative) direction with a linear speed of 2 μm/s (i.e., 20 % of the maximum linear speed of the wheel).

The purely reactive decision-making of the predator agents could be formally defined by the following octet:

$A = \{ V_{00L}, V_{00R}, V_{01L}, V_{01R}, V_{10L}, V_{10R}, V_{11L}, V_{11R} \}$ (1)

where V_{00L} and V_{00R} are the linear velocities (as a percentage – within the range [-100%...+100%] – of the maximum linear velocity) of the left and right wheels of the robot for the perceived environmental state <00>, V_{01L}, V_{01R}, V_{10L}, V_{10R}, V_{11L}, and V_{11R} are analogical velocities for the perceived environmental states <01>, <10> and <11>, respectively.

Our *objective* of evolving (via GA) the optimal direct mapping of the four perceived environmental states into respective velocities of wheels could be rephrased as evolving such values of the velocities, shown in the octet in Equation (1), as well as the coevolution of the offset of the sensor, that result in most efficient capturing behavior of the team of predator agents. We shall elaborate on such an evolution in the next section.

2.2 Prey

The prey is equipped with an omnidirectional sensor, with limited range of visibility. To balance the advantage that the omnidirectional sensor gives to the prey, compared to the single-line-of-sight sensor of the predators, the viewing distance of the prey is only 50μm, compared to the 200μm of predators. The maximum speed of the prey, however, is identical to that of the predators. We introduced such sensory and moving contrast to encourage the agents, to evolve as cooperative behavior as they will be unable to capture the prey alone. Another viewpoint suggests that a successful solution to PPPP, defined in such a way, could demonstrate the virtue of MAS as the latter could, indeed, solve a problem that a single predator is unable to solve. The main features of the prey agent are shown in Table 2.

Conversely to the behavior of predators, the behavior of the prey is handcrafted. The prey tries to escape from the closest predator (if any) by running at its maximum speed in the direction that is exactly opposite to bearing of the predator.

2.3. The World

The world is simulated as a two-dimensional square [1600 μm x 1600 μm]. The perceptions, decision making, and the resulting new state (e.g., location, orientation, and speed) of agents are updated with sampling interval of 100ms. The duration of trials is 120 s, modeled in 1200 time steps. We approximate the new state of predators in the following two stages. First, we calculate the new orientation (as an azimuth) from the current orientation, the yaw rate of agents, and the duration of the sampling interval. The yaw rate, is obtained from the difference between the linear velocities of the left and right wheels, and the length of axis between the wheels. Then, we calculate the new position (as two-dimensional Cartesian coordinates) as a projection (in time, equal to the duration of the sampling interval) of the vector of the linear velocity of predators. The vector is aligned with the newly calculated orientation, and its magnitude is equal to the average of the linear velocities of both wheels.

3. EVOLUTIONARY SETUP

We decide to apply a heuristic, evolutionary approach to the "tuning" of the velocities of both wheels for each of the perceived four environmental situations because we are a priori unaware of the values of these velocities that would yield a successful behavior of the team of predator agents. As we briefly mentioned in Section 1, MAS, as a complex system, feature a significant semantic gap between the hierarchically lower-level properties of the agents, and the higher-level properties of the whole system. Consequently, we would be unable to formally infer the optimal values of the octet of velocities of the wheels of agents from the desired behavior of the team of such agents.

Alternatively, in principle, we could have adopted another – deterministic – approach, such as, for example, a complete enumeration of the possible combinations of the eight velocities of wheels. If each of these 8 velocities is discretized into, say, just 40 possible integer values ranging from -100% to +100%, then the size of the resulting search space would be equal to 40^8, or about 6.5×10^{12}. This would render the eventual "brute force" approach, based on complete enumeration of possible combinations of values of velocities computationally intractable.

GA, on the other hand, is a nature-inspired heuristic approach that gradually evolves the optimal values of set of parameters in a way similar to the evolution of species in nature. GA has proved to be efficient in finding optimal solution(s) to combinatorial optimization problems featuring large search spaces [11] [12] [13]. Thus, consonant with the concept of evolutionary robotics [10], we adopted GA to evolve the optimal values of the eight velocities of the wheels of predators that result in an efficient behavior – presumably involving exploring the environment, surrounding-, and capturing the prey – of the team of predators. The main features of the adopted GA – genetic representation, genetic operations and fitness function are elaborated below.

3.1 Genetic Representation

The decision-making of the predator agents, is represented genetically in GA as a "chromosome". The latter consist of an array of eight integer values of the evolved velocities of wheels of the agents and an additional allele representing the angular offset for the sensor to the longitude axis of the agent.

The values for the velocities are constrained within the range [-100%…+100%], and are divided into 40 possible discreet values, with an interval of 5% between them. The decided number of discrete values (and, the interval between these values, respectively) provides a good trade-off between the precision of "tuning" and the size of the search space of GA. The angular offset is defined in range between 2 and 40 degree, counter clockwise rotation. The population size is 400 chromosomes. The breeding strategy is homogeneous in that the performance of a single chromosome, cloned to the decision-making mechanisms of all predators is evaluated.

3.2 Genetic Operations

Binary tournament is used as a selection strategy in the evolutionary framework. It is computationally efficient, and has proven to provide a good trade-off between the diversity of population and the rate of convergence of fitness. In addition to the tournament selection, we also adopted elitism in that the four best-performing individuals survive unconditionally and are inserted into the mating pool of the next generation. Also, we implemented – with equal probability – both one- and two-point crossover. The two-point crossover results in an exchange of the values of both velocities (of the left- and right wheels, respective) associated with a given environmental state. This reflects our assumption that the velocities of both wheels determine the moving behavior of the agents (for a given environmental state), and therefore – they should be treated – as an evolutionary building block – as a whole. Two-point crossovers would have no destructive effect on such building blocks.

3.3 Fitness Evaluation

Our aim is to evolve behaviors of the team of predators that are general to multiple initial situations, rather than a behavior that is specialized to a particular one situation. To force such an evolution, in the implementation of our simulation environment, we introduce 10 different initial situations and evaluate each of the evolved chromosome on them. In each of these situations, the prey is located in the center of the world, and oriented in a random direction. The predators are scattered in a small cloud situated south of the prey. The distance between the center of the cloud and the prey gradually increases (2 μm per situation) with the increase of the numerical identifier (from 0 to 9) of the current situation. This introduces a gradual increase in the difficulty of the situations, the agents are place in. This way of *incremental* evolution employed in an attempt to improve the computational efficiency of GA as initially the agents are not expected to solve more than a few initial situations. A snapshot of a sample initial situation is shown in Figure 3.

The overall fitness is the sum of the fitness values, scored in each of the 10 initial situations. For a successful situation (i.e. the predators manage to capture the prey during the 120 s trial), the fitness is equal to the time needed to capture the prey. If the initial situation is unsuccessful, the fitness is calculated as a sum of (i) the closest distance – registered during the entire trial – between the prey and any predator and (ii) a penalty of 10,000. The former component is intended to provide the evolution with a cue about the comparative quality of the different unsuccessful behaviors. We verified empirically that this heuristic metrics quantifies the "near-misses" well, and correlates with the chances of the predators – pending small evolutionary tweaks in their genome – to successfully capture the prey in the future. The second component is introduced with the intension to heavily penalize the lack of success of predators in any given initial situation. We believe that it should "encourage" the predators to search for such a general behavior that yields a successful resolution of as many initial situations as possible, preventing their "fixation" on eventual improvements in already successfully solved situations.

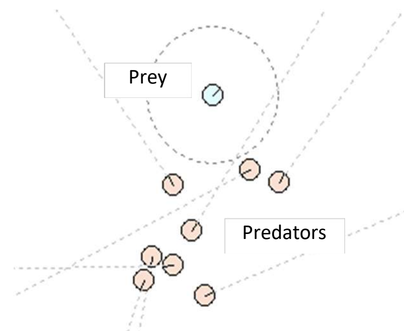

Figure 3: A snapshot of a sample initial situation

Lower fitness values correspond to better performing team of predator agents. Since we are aiming to discover the best possible solution to the problem, there is not restriction to end the evolution upon reaching certain fitness values. Instead the termination criteria is either 200 generations or stagnation of the fitness for 32 consecutive generations – whichever comes first. The main parameters of adopted GA are shown in Table 3.

Table 2: Main Parameters of GA

Parameter	Value
Population size	400 chromosomes
Selection	Binary tournament
Selection ratio	10%
Elite	Best 4 chromosomes
Crossover	Both single- and two-point
Mutation	Single-point
Mutation ratio	5 %
Fitness cases	10 initial situations
Duration of the fitness trial	120 s per initial situation
Fitness value	Sum of fitness values of each situation: (a) Successful situation: time needed to capture the prey (b) Unsuccessful situation: 10,000 + shortest distance between the prey and any predator
Termination criteria	(# Generations>200) or (Stagnation of fitness for 32 consecutive generations)

4. EXPERIMENTAL RESULTS

In this section we will present the experimental results of evolving the optimal values of the velocities of the motors and the angular offset of the sensor that yield an optimal successful behavior of the predator agents. We will evaluate the proposed approach in terms of efficiency and consistence of evolution, generality of evolved behavior, and robustness to noise.

4.1 Evolving the predator agents

As Figure 4, 5 and 6 illustrate, just by adding the offset, the results in number of successful initial situations and overall fitness dramatically improves compared to the standard definition, where there was no angular offset. On average, the predators were able to resolve all 10 initial situations until 10th generation. From all 20 independent runs of GA, there is one distinguished solution, which offers 8 successful situations, out of 10(from now on we will refer to is as run #9), on the first generation. That individual chromosome has an offset of 20 degrees. Unfortunately, it is not the one with the best overall fitness after from all the runs.

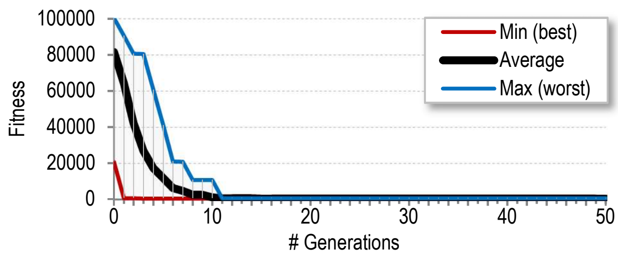

Figure 4: Convergence of the best fitness of 20 independent runs of GA.

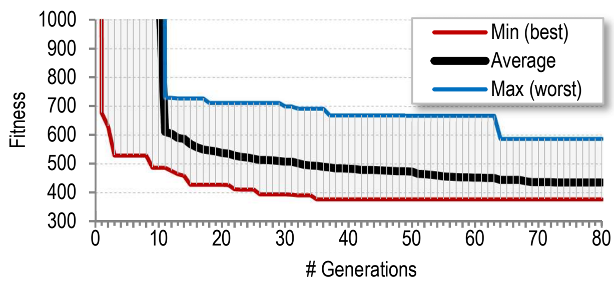

Figure 5: A more detailed illustration of the convergence of the best fitness of 20 independent runs of GA.

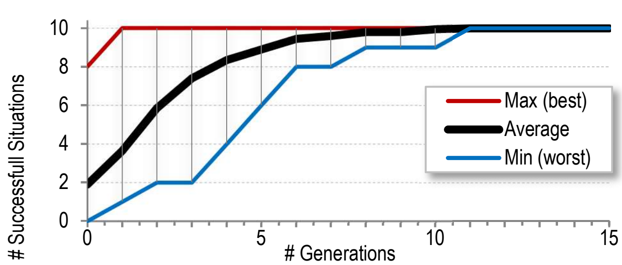

Figure 6: Convergence of the number of successful situations of 20 independent runs of GA.

The most efficient evolution and most general behaviors were obtained for sensory offset of 18 degrees (run #5). While a bit slower in evolution, by reaching 10 solutions on 8th generation (second generation for run #9), this individual manages to reach a fitness of 377, compared to 417 for the former.

In figure 7 we can see the angular offset for the best chromosome from each of the 20 runs of GA. From the results we can deduce that the best solutions in regards of speed to capture the prey are found with angular offset between 18 and 22 degrees, even though successful behavior can be evolved for any offset in the range.

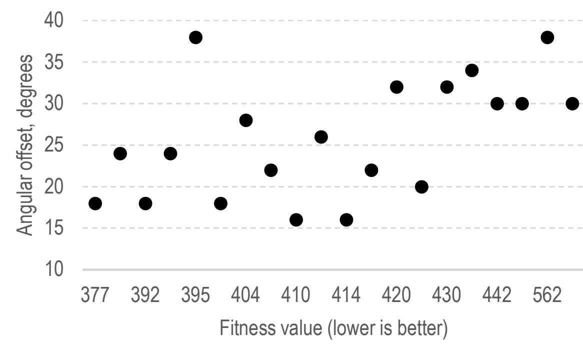

Figure 7: Different values for the angular offset and the corresponding fitness for the evolved chromosome.

Two of the runs resulted in finding a solution with offset of 38 degrees – run number 6 and 17, but although having the same offset, there is a big difference in their fitness – 562 and 395 respectively. This shows that there may be multitude of results for the evolution with the same offset, as a longer evolution might yield better results.

It's interesting to note that while some of the runs experienced a wide variation of sensory offsets, as shown on figure 8, that's not the case for others like the run with best fitness – run #5 or the previously discussed run 6. We see that having a diverse set of angle offsets is not needed rather we are searching for the correct configuration that shows best behavior for given mapping of the wheels' motors as, from generation one, until the stagnation criteria was met, the angle remained constant with a value of 18 degrees.

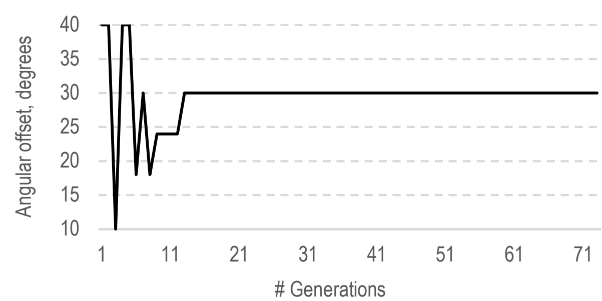

Figure 8: Evolution of sensor offset for run #1

4.2 Robustness to perception noise.

To finish evaluating the efficiency of the genetically generated solutions, we will test the reaction of the best chromosome from every independent run of GA to random perception noise. We introduced two types of noise – false positive (FP) and false negative, respectively. The former results in either of the two bits of perception information to be occasionally (with given probability) read as "1" regardless of whether an entity is detected in the line of sight of the predators or not. False negative noise (FN) results in readings of "0" even if an entity is seen. We focused on these types of noise as we assume that the perception subsystem of predators, yet being rather simple, would require an appropriate thresholding of the sensory signal. A combination of unfavorable factors, such as incorrectly established threshold, variable noise levels in the environment or in sensors would result in the considered two types of perception noise. Figures 9 and 10 show the variation of number of successfully solved situations to different levels of noise, respectfully for false positive noise and false negative noise.

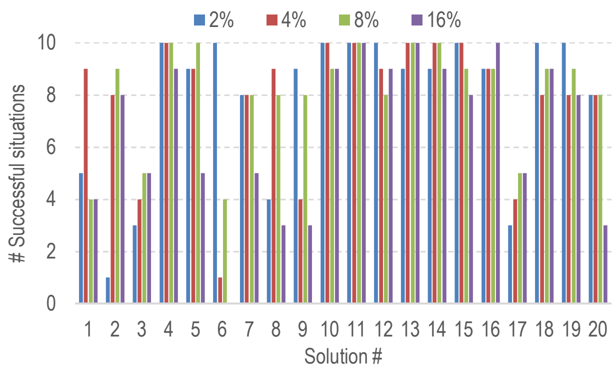

Figure 9: Robustness to false positive noise of each of the 20 best evolved solutions.

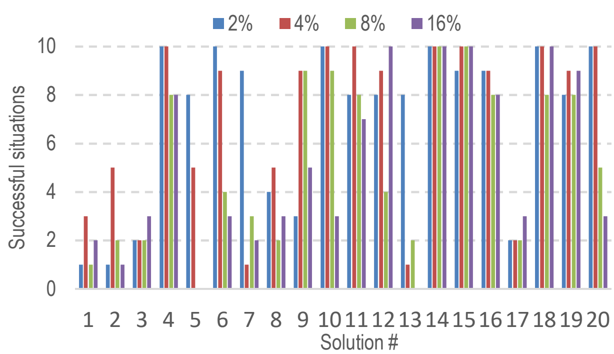

Figure 10: Robustness to false negative noise of each of the 20 best evolved solutions.

Run #5 and run #9, which we previously considered best due to optimal fitness and fastest evolution, do not give good results when noise is introduced. Most of the tests, they fail to solve some of the initial situations as the cases with false negative noise give the worst results, where the agents from run #5 cannot catch the prey in any of the situations and the evolved agents from run #9 are successful in only half of the situations for 16% and 9 situations for 8% noise. Instead, as more robust, the mapping of agents from run #11 and run #14, emerge as more robust to FP noise and FN noise, respectfully. The controller from run #11 manages to solve the tests with false positive noise perfectly, while maintaining satisfactory performance in the tests with false negative noise, being able to solve from 7 to 10 initial situations, depending on the level of noise. On the contrary, the agents from run #14 solve the situations with false negative noise perfectly, while being able to solve 9 out of 10 initial situations in the situations with false positive noise, which gives the best overall performance. It should be noted that run #11 evolved to use an angle offset of 18 degrees and run #14 offset of 20 degrees, which confirms our previous results for best offset.

5. DISCUSSION

With this research, we've shown that introducing an offset to the viewing sensor beam helps for a more effective behavior of the team of agents and increases the efficiency of the evolution of GA. This effect is possible, because in its essence, the offset helps to implicitly determine the position of the prey in relation to the chasing agent if the prey goes out of sight. Having a counterclockwise displacement, means that most of the time the prey will be to the left of the predator and a slight turn will allow to locate it again. This allow for faster localization compared to classic case with sensor oriented towards the longitudinal axis, in which the agent will be unsure to which side the prey disappeared.

The experiments determined that an angle of 20 degrees was optimal in robustness to noise and close enough in terms of fitness to the best performing team of agents without noise, having a fitness of 411 compared to 377. We consider this the best configuration for the team of agents. Furthermore, higher values of the offset would imply a higher value of the tangential- and lower value of the radial (i.e., towards the prey) component of the vector of the speed of chasing predator, and consequently, a slower overall chasing speed of the latter.

In the suggested use for medical nano-robots, the task of the agents should be easier, as the "prey" in that case is not necessarily trying to avoid the agents. The complexity comes from the movement of the complexity of the body structure and the inherently larger search space of the three dimensional environment, in which the entities will be located.

6. CONCLUSION

Nano-robots are newly emerging technology, made possible by the rapid technological advancements in the last century. Creating man-made machines on a miniature level, however, shows that there are significant problems to overcome, due to the differences in physics laws and the limited resourced available due to the small size. Furthermore, as medicine is the most prominent field of use for these new machines, they need to be reliable and precise in their work, which requires making no compromises in the quality of their operation. In attempt to solve these restrictions, we employed a variation of the predator-prey pursuit problem (PPPP), implementing very simple predator agents, equipped with a single beam sensor with an angular offset to the base longitude axis of the agent, and a simple control of the velocities of their two wheels. The simulated agents are morphologically simple in that they utilize a direct mapping of the perceived environmental states into corresponding velocities for their pair of wheels.

We implemented a genetic algorithm, used to evolve such a mapping of the wheels and angular offset of the sensor, which results in finding such behavior for the team of predator agents that allows capturing the prey in minimal time (optimization by fitness). The results from our unreleased research showed that PPPP could not be solved for more than just a few initial situations by the commonly considered predator agents with a sensor beam aligned with their longitudinal axis. This experiment, featuring a coevolution of the angle of the sensor and the velocities of the wheels, shows that the offset of 18 degrees yields a most efficient behavior of the team of agents in all of the 10 tested initial situations in regard to optimal capture time.

Such a behavior for a team of simple agents can be used in micro and nano-robots, where computational are limited or impossible to implement with current technology [14]. It would be specifically useful in medicinal nano-surgery where it will allow of pinpoint medicine delivery and operations on hostile organisms or mutated tissues (such as cancer cells), on a microscopic level. In our future work, we are planning to employ a three dimensional model which will resemble a more realistic environment such as the human body, and test the capabilities of this method, of evolution for real life applications.

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