Exploration of the Effect of Uncertainty in Homogeneous and Heterogeneous Multi-agent Societies With Regard to their Average Characteristics

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ABSTRACT

In electrical engineering, the deviation from average values of a signal is viewed as noise to the useful measurement. In human societies, however, the diversity of the exhibited characteristics are a sign of individuality and personal worth. We investigate the effect of uncertainty variables in the environment on multi-agent societies (MAS) and the consequences of the deviation, from the average features of the modeled agents. We show the performance of heterogeneous MAS of agents in comparison to morphologically identical homogeneous systems, preserving the same average physical and sensory abilities for the system as a whole, in a dynamic environment. We are employing a form of the predator-prey pursuit problem in attempt to measure the different performance of homogeneous MAS with average parameters and its heterogeneous counterpart. The effects of uncertainty in our work is investigated from the viewpoint of (i) employing a limited number of initial situations to evolve the team of predator agents, (ii) generality to unforeseen initial situations, and (iii) robustness to perception noise. Key statistics are the efficiency of evolution of the successful behavior of predator agents, effectiveness of their behavior and its degradation because of newly introduced situation or noise. Preliminary results indicate that a heterogeneous system can be at least as good as its homogeneous average equivalent, in solution quality at the expense of the runtime of evolution.

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CCS CONCEPTS

Computing methodologies → distributed artificial intelligence; robotics;

KEYWORDS

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

1 INTRODUCTION

Due to the various constraints (e.g. consensus problem, inter-agent credit- assignment problem, computationally heavy evolution due to the large search space, etc.) pertinent to the development of heterogeneous multi-agent systems (MAS) as a distributed problem-solving approach [1], the research on them is underrepresented compared to the alternative homogeneous implementations [2]. The main motivation of our current work is that, to the best of our knowledge, the comparative analysis of the effects of uncertainty and noise in the environment of heterogeneous and homogeneous multi-agent systems is not studied extensively enough. An additional motivation of our research is, consonant with the concept of the "end of average" that appreciates the difference from the (often – mediocre, and sometimes – even non-existing, statistically calculated) average in human societies [3], to investigate the importance (if any) of the diversity of individual capabilities of heterogeneous agents featuring the same average as the (identical) agents in analogous homogeneous systems.

As a model of the typical human being, its performance and efficiency in society, the most common image is characterized by a simple value – the value of the average of abilities of its respective members [3]. The concept is borrowed from electrical engineering where the average usually manifests the useful signal while any fluctuations from it are a result of random noise. For human societies, however, the average (of a given ability of the members of society) is not necessarily seen as a useful signal, but rather as a synthetic, and often – meaningless, value, that is not actually exhibited by the vast majority of the members of society. Similarly, the fluctuations from the average value (of a given ability) are far from noise, but rather – specific variations that characterize the identity and personality of these members and a trait that, in many cases, may contribute to solving challenging new, previously unknown problems.

The *objective* of our research is to investigate the importance (if any) of the average for the efficiency of multi-agent systems as a model (yet, to very a limited extent) of human societies, in uncertain environments. In addition, we should investigate whether the diversity (even at the expense of reduced average) of abilities rather than their average plays an important role in building better-performing multi-agent systems.

The main application areas of MAS are problem solving, simulation, collective robotics, software engineering and modeling of synthetic worlds [4]. For this purpose, we developed heterogeneous MAS that models some of the important aspect of human societies, such as cooperation, collaboration, communication, and division of labor. We are also implemented an evolutionary computing framework – e.g., genetic programming (GP), that could be used to evolve such a behavior of agents that results in best effectiveness (performance) of the multi-agent system as a whole. The use of genetically evolved solutions will make our work more realistic than commonly considered previous work [5] [6]. Further, we will evolve this multi-agent system for various combinations of the individual abilities of the agents (and for various results of the average of these abilities) and investigate the obtained optimal performance of the whole system.

Within the considered context, we will be employing the predator-prey pursuit problem (PPPP) to investigate the effect of the average and diversity on the MAS in evolution of the behavior and performance in an unforeseen, randomly generated environment.

The efficiency of the multi-agent systems will be measured using a few factors – the number of different test scenarios that leads to a positive outcome (capturing the prey), overall fitness of the solution, found through genetic programming, and speed of evolution (the time needed to find an optimal solution for the specified number of test cases). Additionally we will investigate the robustness of the evolved team of agents to newly presented, previously unknown initial situations.

2 PROPOSED APPROACH

In this section, we will describe, in detail, the implementation of the predator and prey agents in the proposed PPPP, as well as the implementation of the world.

The implementation of the proposed PPPP features a team of superior in terms of perceptions, but inferior in terms of moving abilities agents - predators, attempting to capture a single prey.

The simulated environment is a two-dimensional infinite toroidal world. We expect that the changes introduced into the heterogeneous system will encourage the agents to evolve a more complex behavior and more complex (yet implicit) interactions between the predator agents in order to solve the more difficult task.

2.1 Predator Agents

The team of predators consists of four agents with inferior moving abilities, compared to the prey. We do not consider the case in which the agents are superior in terms of speed, as capturing the prey in that condition seems to be trivial and a single agent will be able to accomplish it. In addition, if the prey agent is absolutely superior, it will be very hard or even impossible for our team of predators to capture it. Therefore, to give the chasing predators a chance to complete the given task, we equip them with vision sensors featuring a greater range than the prey. Unlike the prey agent, the behavior of the predators is not fixed, but evolved, which would allow an emergence of collective strategies of the team of predators as a result of evolution of their behavior. The agents can adjust their speed to 0, 0.25, 0.5, 0.75 and 1.0 of their maximum speed. We have chosen an arbitrary value of 450 for the average view range and 16 for the average speed. The homogeneous system will be serving as our control group and take on the average values, while the homogeneous system will be tested with different values for the range of the view sensor. The main features of the predator agents are shown in Table 1, for the homogeneous system, and in Table 2, for the heterogeneous one. The heterogeneous system features two groups of two, morphologically identical agents. Each of them will have a value of sensor range, such as to keep the average of all four agents of 450 – equal to the range of sensors of predators in homogeneous MAS.

Table 1: Features of predators in homogeneous MAS

Feature	Value
Number of predator agents	4
Diameter, mm	50
Max speed of predator agents, mm/s	16
Type of sensor	Omnidirectional vision
Range of visibility of the sensor, mm	450

Table 2: Features of predators in heterogeneous MAS

Feature	Value
Number of predator agents	4
Diameter, mm	50
Max speed of predator agents, mm/s	16
Type of sensor	Omnidirectional vision
Range of visibility of the sensor of the two agents in Group 1, mm	*300-400*
Range of visibility of the sensor of the two agents in Group 2, mm	*500-600*

2.2 Prey

The prey is a single agent with fixed behavior using a handcrafted escaping strategy [7] when a predator agent is visible and random wandering when there is not imminent threat. The maximum moving speed of the prey is higher than the maximum speed of the predators. The movement of the prey is continuous; it can turn left or right at any angle from its current direction. When chased, the prey is able to run at full speed, until its adversary is no longer in perception range. Features of the prey agent can be seen in Table 3.

Table 3: Features of prey

Feature	Value
Number of prey agents	1
Diameter, mm	40
Max speed of predator agents, mm/s	24
Type of sensor	Omnidirectional vision
Range of visibility of the sensor, mm	200

2.3 The World

The world is simulated as a two dimensional surface with size of 1600x1040 mm (scaled). The perception range, decision making and resulting new state (location, orientation and speed) of the agents are updated with sampling interval of 500ms.

3 EVOLVING THE PREDATOR AGENTS

We will be using a previously developed implementation of a strongly-typed GP framework [7] for homogeneous MAS. We intend to achieve heterogeneity in the behavior of agents by means of exploiting their morphological – rather than their genotypic – differences. The possibility to exploit such a polymorphism to obtain a behavioral heterogeneity of genetically identical (homogeneous) predators allows us to employ the same evolutionary framework to evolve the team of predators in both – homogeneous and heterogeneous systems. We view this as an important argument in favor of the fairness of the presented comparative analysis of both systems.

3.1 Genetic Representation

The controlling program of predators is a set of IF-THEN stimuli-response rules. They are represented as Document Object Model (DOM) parse tree structures, featuring, in addition, a plain-text XML encoding [8]. The DOM/XML representation allows us to perform the genetic operations using the API of an off-the-shelf, programming-language-neutral, XML DOM parser.

3.2 Sets of Functions and Terminals of GP

The set of functions and terminals of the adopted GP are identical to the ones used in our previous work [7]. They are shown in Tables 4 and 5, respectively.

The execution of the following example (in pseudocode) of a behavioral stimuli-response IF-THEN rule would result in turning the predator 22 degrees to the right and setting its speed to 0.5 of maximum if its distance to the prey is shorter or equal to 316:

```
if (Prey_d<=316) then begin
  Turn(22);
  Go_0.5;
end;
```

The breeding strategy is homogeneous in such a way that the performance of a single chromosome, cloned to all four agents is evaluated. The gene pool consists of 400 chromosomes.

Table 4: Function set of GP

Designation	Meaning
IF-THEN	stimuli-response IF-THEN rule
LE, GE, WI, EQ, NE, +, -	≤, ≥, Within, =, ≠, +, -

Table 5: Terminal set of GP

Category	Designation	Explanation
Sensory abilities	Prey_d; Peer_d	Distance to the prey and to the closest agent, *mm.*
	Prey_a; Peer_a	Bearing of the prey and of the closest agent, *degrees*
	PreyVisible; PeerVisible	True if prey (predator) agent is "visible", false otherwise
State variable	Speed	Speed of the agent, *mm/s*
Ephemeral constants	Integer	
Moving abilities	Turn(α)	Turns relatively to α degrees (α>0: clockwise)
	Stop, Go_1.0	Sets speed to 0, or to maximum, respectively
	Go_0.25, Go_0.5, Go_0.75	Sets speed to 25%, 50%, 75% of maximum

3.2 Genetic Operations

The adopted GP employs a binary tournament selection as we consider it both computationally efficient and simple to implement. We also adopted elitism in that the four of the best performing chromosomes of the current generation are copied unconditionally and are inserted in the mating pool of the next generation. A strongly-typed crossover operation is defined in a way that only the nodes of the same data type (i.e., featuring an identical DOM/XML tag) from both parents can be swapped. Sub-tree mutation is also allowed, in a strongly typed way – a synthetically correct subtree can replace a random node in the genetic program.

3.3 Fitness Evaluation

In order to evolve a general enough solution to the problem, the behavior of the team of predators is evaluated on 10 initial situations. This allows us to avoid overfitting of the evolved agents to any particular situation, and to create a more robust system. The population includes 400 chromosomes (representing 400 IF-THEN stimuli-response rules), initially generated randomly. Each of these chromosomes is cloned to all four predator agents and the behavior of the team of the agents, controlled by the given chromosome is evaluated based on the efficiency of capturing (if any) the prey in each of the 10 initial situations. In each of these situations, the prey is located in the center of the world and oriented in a random direction. The predator agents are randomly placed and randomly oriented on the field in such a way, as to have a diverse set of situations, to avoid overfitting for a certain way of their disposition. Because, initially, the agents are unable to solve all 10 initial situations, to improve the computational efficiency of GP, the first trial starts with 2 tested initial situations and the number of tested situations is increased by 2, every time the agents manage to solve *n-1* situations, where *n* is the number of currently tested situations.

The overall fitness for the particular chromosome is calculated as an average of the fitness values scored in each of the test situations for that run. The fitness each of the situations is the sum of the average distance to the prey, average energy consumption and elapsed time for the trial. To avoid generation of very complex controllers, a parsimony pressure is applied to each chromosome, equal to 0.1xC, where C is the complexity of the chromosome estimated as the number of nodes in its parse-tree representation.

Lower fitness values represent better performing team of predator agents. The termination criteria is the fitness value lower than 300 and 10 successfully resolved initial situations (for successful runs of GP), or stagnation of fitness for 10 consecutive generations or 50 total generations tested (for unsuccessful runs). The main features of GP are shown in Table 6.

Table 6: Main features of GP

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	1%
Fitness cases	10 initial situations
Duration of the fitness trial	600 cycles per initial situation(300 seconds with 500ms sampling interval)
Fitness value	Sum of the average distance to the prey, average energy consumption and elapsed time for the trial. In addition, parsimony pressure is applied for large controllers.
Termination criteria	(Fitness value<300 AND 10 successful situations) or (# Generations>50) or (Stagnation of fitness for 10 consecutive generations)

4 EXPERIMENTAL RESULTS

Our experiments involve 40 independent runs of GP for each one of the test cases of PPPP. Each test case involves different configuration of agents, and for heterogeneous system this implies a different combination of ranges of sensors of predators belonging to the two groups of agents. We considered a change of the range in intervals of 50 (e.g. 400-500, 350-550, 300-600) while keeping the value of the average of the ranges constant (i.e., 450). In this section we will present the features of the behaviors of the team of predators, obtained from the evolution of an average homogeneous system, compared to the solutions of each of the heterogeneous configurations, evolved over 50 generations of GP. Additionally, we will review the generality of the evolved predator agents, as well as their robustness to a changing environment. We will discuss the problems that arise from the proposed approach to create a heterogeneous system based on disparity in morphology rather than changes in genotype of the predator agents and how they affect the general performance in a noisy or uncertain environment.

4.1 Evolution of the Homogeneous System

On average, the homogeneous system is able to solve all 10 initial situations only in 3 out of 40 (i.e., 7.5%) of runs. The evolution shows consistent development of controllers of predator agents, with fitness level averaging around 447 and with worst solution having a fitness of 465. However, best solution of the series ends the trial with fitness of 235 and 10 successful initial situations in twenty-first generation, as illustrated in Figures 1 and 3.

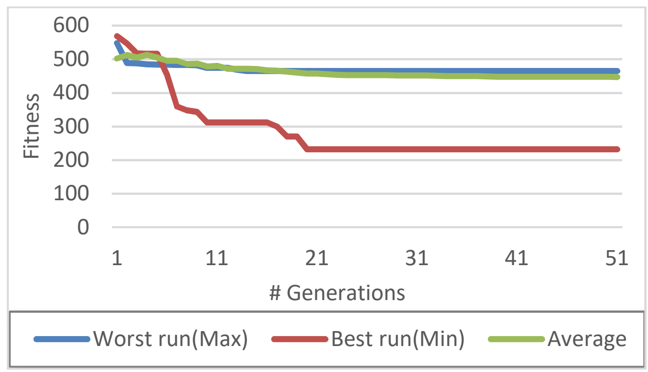

Figure 1: Convergence of fitness of the homogeneous MAS

The result of this experiment demonstrates that, while the best run is able to solve the problem with a reasonable effectiveness, the efficiency of evolution is rather poor, as the majority of the independent runs of GP could not reach the desired results. Moreover, as shown in Figure 2, even some of the runs could not resolve more than one initial situation.

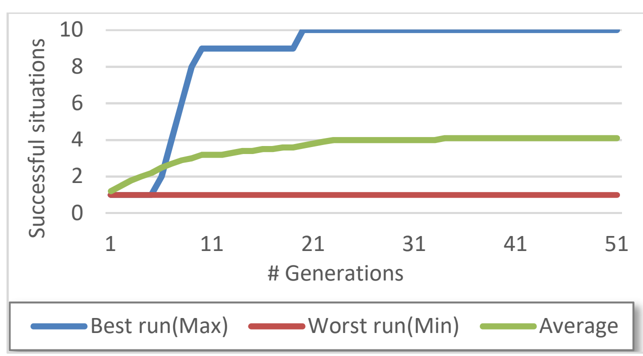

Figure 2: Dynamics of number of successfully solved initial situations by the homogeneous MAS.

We view this inconsistency as an indication that the homogeneous system – for the considered combinations of perception- and moving abilities of the entities – features a rather difficult, rugged fitness landscape, and the evolution often struggles to discover the areas of the optimal fitness in it. In particular, as the analysis of the evolved behaviors of the predators, the shorter range of sensors often hinders the formation of the behavior pattern (surrounding), required to capture the prey and this pattern is seldom discovered by the successfully evolved team of predators.

4.2 Evolution of the Heterogeneous System

In our quest to discover such a heterogeneous system that would result in a better efficiency of evolution compared to that of the homogeneous system, we conducted experiments with evolution of three different configurations of predator agents as shown in Table 7. Notice that the average of the range of visibility of sensors of the agents in these three configurations of the heterogeneous system is constant. Moreover, it is equal to the range of visibility of sensors of predators in the considered homogeneous MAS.

Table 7: Three experimental configurations of the ranges of visibility of sensors of the agents in heterogeneous MAS

Experimental Configuration (Test Case)	Range of visibility of sensors, mm		
	Group 1 (two agents)	Group 2 (two agents)	Average of all four agents
A	400	500	450
B	350	550	450
C	300	600	450

The results are very diverse – some configurations show better evolution than the average (homogeneous) system, while others cannot compare at all. Some of the configurations manage to evolve better solutions than the average, with fitness values converging around 425 (compared to 447 for the average systems) and the solved initial situations converging around 5 (compared to 4 in average MAS). Other configurations of the heterogeneous system show poor results in terms of successfully solved situations and fitness, as illustrated in Figures 3 and 4. These results demonstrate that the improvement of the overall performance of the heterogeneous MAS, in regard to the average value of a homogeneous MAS, vary depending on the difference between the average values of their perception abilities and the desired optimal values of the implementation of the agents (e.g. in general, based on financial, available resources or some other constraints). In the considered context, the most prominent results are exhibited by multi-agent systems with sensor variations between 10 and 20 percent of the range of visibility of the predators in the average (homogeneous) system. More significant disparities in perceptions of the heterogeneous predators seem to be detrimental both for the efficiency of evolution and effectiveness of the evolved behavior of agents in the considered instance of MAS.

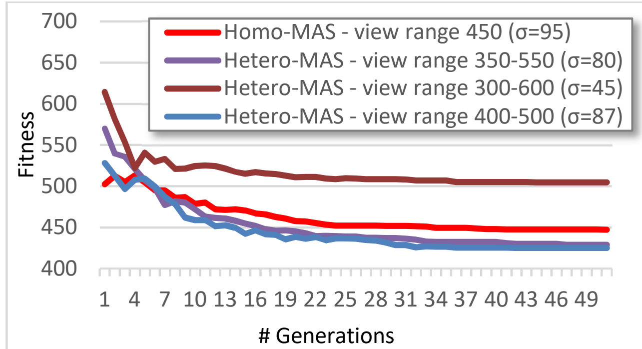

Figure 3: Convergence of the average fitness for different configurations of evolved MAS. On generation #50 the P-value is $1{,}91 \times 10^{-11} \ll 0.05$

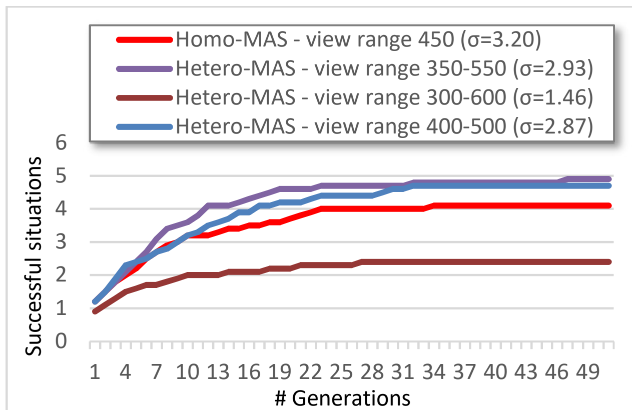

Figure 4: Dynamics of number of successfully solved initial situations. On generation #50 the P-value is $1{,}56 \times 10^{-83} \ll 0.05$

From all 4 test cases, the one of the heterogeneous MAS where the visibility range of predators is 350 and 550 (configuration B, shown in Table 7), respectively, demonstrates both (i) most consistent evolution and (ii) highest number of solved initial situations. We will compare the best evolved behavior of predators of this heterogeneous configuration with the best behavior of the homogeneous system. The heterogeneous system with predator agents featuring range of visibility 350 and 550 (configuration B) manages to solve all 10 initial situations at generation 34 with a fitness value of 264, while the system with a range of visibility of predators 400 and 500, respectively (configuration A) solves 10 initial situations at generation 15 with a fitness of 223. On the other hand, the homogeneous system with an average range of visibility of predators (i.e., 450) solves all 10 initial situations at generation 20 and fitness of 232. The increased computational effort of evolution is somehow expected, given the significant inflation of the search space of the heterogeneous system. This inflation is caused by the fact that the agents are not separated in two groups of morphologically similar entities and their position in the world has an effect on the outcome of the attempt to solve the task, while in the homogeneous system all agents are the same and their position does not matter. Moreover, despite the increased search space, the results remain comparable - as shown in Table 8, the heterogeneous MAS is more successful in solving more than one initial situation even though the end results are the same – three out of four systems manage to evolve around 3 individuals that solve all 10 initial situations.

Table 8: Average number of successfully solved initial situations.

Successful Initial Situations	Configuration of MAS			Standard deviation σ
	Homo-geneous	Heterogeneous		
		Range of visibility 350 and 550 (Test Case B)	Range of visibility 400 and 500 (Test Case A)	
1	10	5	5	2.88
2	11	7	7	2.30
3	2	5	7	2.51
4	3	2	1	1
5	1	5	5	2.30
6	1	4	2	1.52
7	4	3	5	1
8	1	2	2	0.57
9	4	4	4	0
10	3	3	2	0.57

In addition, we would like to note that the best behavior of predators is evolved in the heterogeneous MAS with range of visibility of predators 400 and 500, respectively, which corresponds to about 10% disparity compared to the average value of 450, used by agents in homogeneous system. Figure 6 illustrates the dynamics of the fitness value and the number of successfully solved initial situations. It is interesting that the evolution actually manages to solve all 10 situations at generation 7. However, because the fitness value at that point does not meet the termination criterion of 300, the evolution proceed further until, at generation 15 both the fitness value (223) and the number of successful situations (10) satisfy these criteria.

5. HETEROGENEOUS MAS FEATURING AN UNEQUAL SIZE OF GROUPS OF PREDATORS

From what we have observed so far, the heterogeneous MAS shows promising results in surpassing the capabilities of the average homogeneous system, though the increase in performance is not significant. Considering the small number of agents – just four – the advantage of using agents with greater sensor abilities may not be sufficient to compensate the drawbacks of having more myopic agents in the same team of predators. Indeed, the two superior agents would not be sufficient to capture the prey in PPPP, as at least three predators (i.e., a "critical mass") would be needed to surround the prey from all sides of the world. In an attempt to investigate whether the issue of critical mass of predators is relevant to the considered case of PPPP, we introduce divide the predators into two groups with unequal number of members as follows: one group of three agents with increased (above the average) sensory capabilities and one group of one inferior agent with lower than average range of visibility, and vice versa. Tables 9 and 10 show the two variants of such grouping. We will conduct additional experiments with these two variants of configurations of MAS, and will refer to them as unbalanced configuration #1 and #2 from now on.

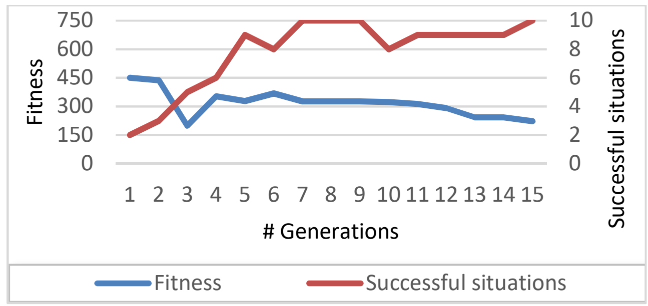

Figure 6: Evolution of the best behavior in heterogeneous MAS with range of visibility of predators 400 and 500, respectively

Table 9: First variant of the configuration of heterogeneous agents featuring an unequal size of groups

Group #	Number of agents	Range of visibility, mm	Average range, mm
1	3	400	450
2	1	600	

Table 10: Second variant of the configuration of heterogeneous agents featuring an unequal size of groups

Group #	Number of agents	Range of visibility, mm	Average range, mm
1	3	500	450
2	1	300	

The trend of solving more of the cases with 3 to 9 initial situations remain, even for the MAS, where 3 of the agents have lower than average sensory abilities, as 20% of the runs manage to solve 9 initial situations, compared to 17,5% in the average MAS. Table 11 shows the success rate of the newly tested configurations of MAS.

We would like to note that in the unbalanced configuration #2, the number of successfully evolved individuals that solve 10 initial situations, significantly increases, however, at the cost of worse fitness values. Most of the evolved solutions for the improved systems were able to solve 10 initial situations and complete the evolution with fitness greater (worse) than 300 – one of the termination criteria, after which they regress to being able to solve less of the initial situations. In addition, for unbalanced configuration #2, there was an individual that stand out from the other solutions, which completed its evolution with great results by having fitness of 159 and 10 successfully solved initial situations, with small regression in the first few generations. Figure 7 shows the evolution of that individual.

Table 11: Success rate (in %) for each initial situations count for the unbalanced configuration compared to average in percentage of total runs.

Successful Initial Situations	Configuration of MAS		
	Homo-Heterogeneous	Heterogeneous	
		Unbalanced Configuration #1	Unbalanced Configuration #2
1	100	100	100
2	75	90	85
3	47,5	67,5	60
4	42,5	62,5	42,5
5	35	50	35
6	32,5	45	27,5
7	30	32,5	25
8	20	25	25
9	17,5	12,5	20
10	7,5	5	12,5

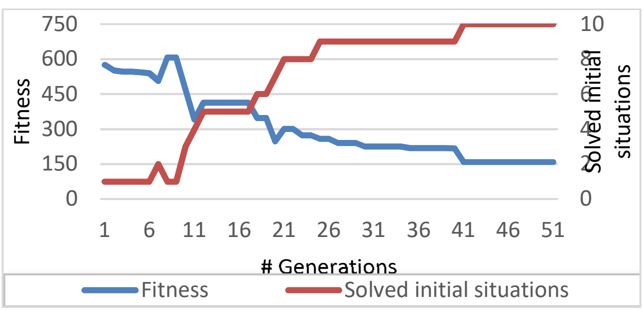

Figure 7: Evolution of the best individual in unbalanced configuration #2.

Even though unbalanced configuration #1 results in lower probability of success, manifested by the lower number of evolutionary runs that solve all 10 initial situations, it produces a notable individual on its own. One of the runs managed to satisfy the termination criteria, with fitness of 260 in only 16 generations, compared to 20 for the best homogeneous (average) system. The evolution of that run is shown in Figure 8.

6. GENERALITY AND ROBUSTNESS

6.1 Generality of Evolved Behavior of Predators

We investigated the generality of the best evolved behaviors of predator agents in different configurations of MAS. The generality, in our experiments is estimated by the number of successfully resolved of 1,000 initial situations, containing the 10 situations employed for the evolution of predators, plus 990 newly introduced situations. The experimental results are shown in Table 12.

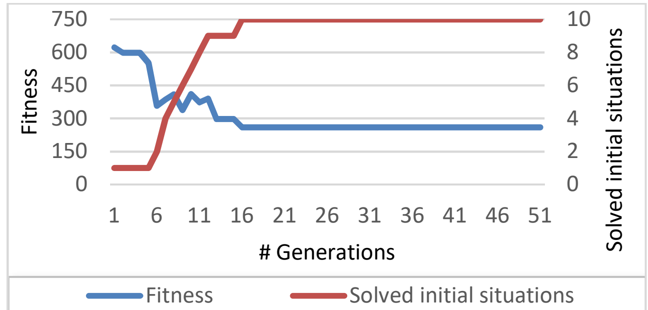

Figure 8: Evolution of the sample individual in unbalanced configuration #1.

Table 12: Generality of evolved behavior of predators to newly introduced 990 situations

Configuration of MAS	Range of Visibility of Predators	# Successful Situations (out of 1000)	Success rate
Homogeneous	4 x 450 mm	736	100% (base)
Heterogeneous A	2x400 mm and 2x500 mm	660	90%
Heterogeneous B	2x350 mm and 2x550 mm	533	72%
Unbalanced #1	3x400 mm and 1x600 mm	549	75%
Unbalanced #2	3x500 mm and 1x300 mm	461	63%

As a base for comparison, we used the number of situations, successfully solved by the homogeneous system (736 situations). Because for the same initial situation, the number of combinations of four heterogeneous agents divided into two groups of two identical agents is 4!/2!x2! = 6, theoretically the total number of possible initial situations in heterogeneous systems A and B is 6 times (4 times for unbalanced situations #1 and #2) higher than that of homogeneous MAS. Consequently, in order to provide the heterogeneous agents with an equal opportunity to learn (how to capture the prey) as the agents in homogeneous systems, we should have evolved them on 6 times higher number of initial situations, i.e., 60 initial situations.

Because we evolved all the systems under the same setup of the evolutionary framework, we, to some extent, expected the inferior generality of the heterogeneous systems. Nevertheless, the heterogeneous systems A featuring a lower disparity of range of visibility of predators (400 mm and 500 mm, respectively) solves 90% of initial situations that are solved by homogeneous system. Also, it is interesting to note that the unbalanced system #1, with the critical mass of 3 myopic, below average (range of visibility 400 mm) heterogeneous agents is more general than that featuring three longsighted, above the average predators (range of visibility 500 mm). In our future work we are planning to investigate whether the (significantly slower) evolution on increased number of initial situations would result in more general heterogeneous teams of predator agents.

While introducing noise to the environment or hardware errors to the agents is the most obvious way to test for robustness of the evolved controller solutions, we will introduce a simpler way, first

6.2 Robustness to Noise

To investigate the robustness of the team of predators, evolved in noiseless environment, would degrade when subjected to perception noise, we introduced a uniform perception noise of up to 5% to both the distance (perceptions Prey_d and Peer_d, shown in Table 5) and bearing (Prey_a and Peer_a) of the perceived entities in MAS. Figure 9 illustrates the variations of the number of solved initial 1,000 (including 10 used for evolution, and 990 newly added) situations for different levels of perception noise. For most of the considered configurations of MAS, the noise results in anomalous increase of the number of successfully solved situations. Because the actions of predators (e.g., "Turn 22 degrees to the left", "Go with 50% of max speed", "Turn 10 degrees to the right", etc.) are a result of execution of alternating stimuli-response rules (corresponding to the instantly perceived, dynamic environment), and therefore, the behavior of agents – seen as a sequence of actions – is rather discrete (jerky) [7], a possible explanation of this anomaly is in the favorable effect of the noise-induced *dithering* (smoothing) on such a behavior. We are planning a more in-depth investigation of why and how dithering facilitates a better behavior of predators in unforeseen situations. Moreover, we intend to investigate the conditions (if any), at which the generality of the multi-agent systems could be improved by adding a certain amount of perception noise.

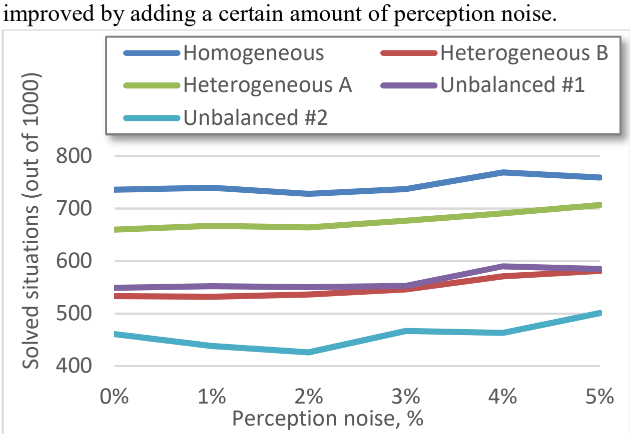

Figure 9: Robustness to perception noise in 1000 initial situations.

Due to the trend that number of successfully solved situations increases with noise, we decided to make one additional test of the two best chromosomes – homogeneous and heterogeneous A. We have tested with 25% noise. The results show that the homogeneous system suffered a regression to only 596 solved situations, while the heterogeneous system managed to solve 843 out of 1000. It shows 14% increase compared to the base of 736.

7. CONCLUSION

In our work we analyzed the performance of homo- and heterogeneous multi-agent systems modeling the predator-prey pursuit problem. All considered systems featured identical average values of the respective perception abilities of predator agents. The experimental results indicate that both (i) the speed of evolution of the successful capturing behavior of predator agents, and (ii) the effectiveness (i.e., its fitness value) of the best-evolved behavior, the heterogeneous MAS are improved, using different methods and techniques, in such a way that it performs better than its homogeneous counterpart. We have demonstrated that the heterogeneous system featuring a deviation of the perception abilities of predator agents of about 10% from the average, could be evolved faster and could result in a better performing team of agents. We also showed that by implementing a team of agent that is big enough to potentially solve the problem alone (i.e., critical mass), the evolution of even better performing team of agents could be achieved even faster. The homogeneous system, however, is more general, in that it is able to successfully resolve the higher number of unforeseen initial situation. The robustness to introduced noise, however, depends on the level of the noise. With high levels of noise, the heterogeneous system shows results that are more consistent and more efficient. One of the reasons for the inferior robustness of heterogeneous systems to uncertainty is that the space of possible combinations of initial situations is significantly larger than that of the homogeneous system. Evolving both types of systems on the same number of initial situations might result in under-representation of the training cases for the heterogeneous system. However, increasing the number of initial situations used for the evolution of the latter would inevitably result in increase of the computational overhead of simulated evolution. In our future work we are planning to investigate the trade-off (if any) between the computational overhead of evolution and the robustness to uncertainty of heterogeneous systems. An eventual success in this direction would allow us to verify our hypothesis that – similarly to the human societies – the disparities in individual capabilities of agents are more important for the success of the team of agents than maintaining identical, "average" agents.

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