Lab 9: Task Allocation in Multi-Robot Systems

This laboratory requires the following equipment:

- C programming tools (gcc, make)
- Webots simulation software, Webots User Guide, Webots Reference Manual

Depending on your programming skills, the laboratory duration might require an effort of up to three hours and assistance will be provided correspondingly during the same time window. We encourage you to take notes during the course of this laboratory to aid in the exams. A solution will be posted a few days after the lab session.

1.1 Office hours

Additional assistance outside the lab period (office hours) can be requested using the dis-ta@groupes.epfl.ch mailing list.

1.2 Information

In the following text you will find several exercises and questions. The type of question is indicated between parentheses:

- The notation S means that the question can be solved using only additional simulation.
- The notation Q means that the question can be answered theoretically, without any simulation.
- The notation I means that the problem has to be solved by implementing a piece of code and performing a simulation.
- The notation B means that the question is optional and should be answered if you have enough time at your disposal (the bonus questions can involve a maximal effort of 20 points)

1.3 Division of Labor

This lab is intended to be a simple introduction to two main families of control mechanisms used for task allocation and division of labor in multi-agent systems: ***Threshold-based*** and ***Market-based*** algorithms.

In this lab, we will try to identify and understand some of the subtleties of these methods, their strengths and weaknesses, the trade-offs inherent in their utilization, and what types of situations or problems they are best suited for.

2 Threshold-based Task Allocation Algorithms

A threshold-based stimulus-to-response model is defined by two basic input and output variables as well as by one parameter on which it is built:

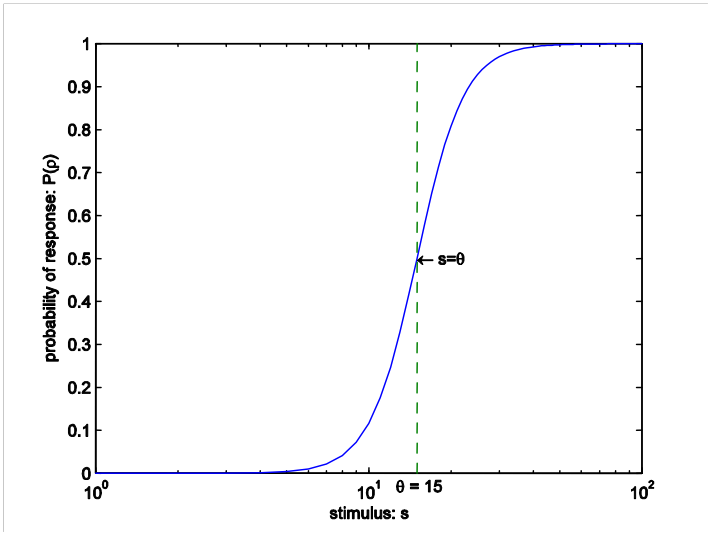
1. **Stimulus (s)**: A quantity which can be measured locally by an agent, corresponding to a (possibly noisy) perception of the current demand or urgency of a given task.
2. **Threshold (θ)**: A parameter internal to an agent, influencing the decision whether or not to act on a given stimulus.

This model, originally proposed for explaining division of labor mechanism in natural societies, has inspired a new family of task allocation algorithms, which we will call threshold-

based allocation algorithms. The response to a given stimulus can be deterministic or probabilistic.

When using a probabilistic response, upon encountering or measuring a stimulus *s*, an agent will decide whether or not to act based on the following formula describing a sigmoid function for the probability of response:

$$T_\theta^{prob}(s) = \frac{s^n}{s^n + \theta^n}$$



The exponent *n* controls the severity of the change from very unlikely to very likely. In the limit $n \to \infty$, the response become deterministic (the probability density is a step function).

These thresholds θ can be either **fixed** or **adaptive**. Fixed thresholds, as their name implies, are never changed, while adaptive thresholds allow for a simplistic type of learning in the system. We also have a choice in how the initial thresholds are assigned; we can give all the agents the same threshold value (**homogeneous**), or we can assign different thresholds to different agents (**heterogeneous**), either at random, according to prior knowledge of the task to be performed, or because the agents become different ("specialized") after a learning process.

- **Experimental Setup**

We will consider a scenario with the following properties: tasks appear randomly in the environment with a certain arrival rate that must be handled by the agents. The number of open tasks that have not yet been handled serves as the stimulus. The stimulus may be measured by the individual agents in various ways – during the exercises we will explore two of the more obvious possibilities. Each agent has a threshold determining what level of stimulus is necessary before it will respond. In our case study, a responding robot executes a random walk and handles events that it encounters; robots whose thresholds are not met will stop or remain stationary.

In the exercises, we will investigate different ways of distributing and maintaining these thresholds and we will study the impact on the group behavior.

2.1 Homogeneous vs. Heterogeneous Threshold Distributions

2.1.1 Perfect Perception

First, we are going to look at a simplified threshold-based task allocation method in a distributed system. In this setting, the stimulus level is announced to the agents via a global broadcast.

You need to download the lab package from the course webpage on Moodle, following these steps:

- Download the `lab09.zip` file from the course's Moodle site, to the directory of your choice.
- Extract the file
- Launch Webots
  (in Ubuntu you may do this from a terminal by entering this command: `webots &`)

1. **(S)** From folder `Threshold`, load `threshold.wbt` in Webots. Clean and compile the provided controller `threshold_epuck.c` and the supervisor controller `threshold_super.c`. At the top of `threshold_super.c` there are several `#define` statements which control the type of simulation that runs. Begin running the simulation and try to understand how the codes work.

2. **(S)** Set the constants defined near the top of `threshold_super.c` for **fixed homogeneously distributed thresholds** with a **global stimulus** announcement (therefore, in the code set `ADAPTIVE 0`, `HETEROGENEOUS 0`, and `GLOBAL_STIMULUS 1`). This means that every agent will have the same threshold value, and it will not change during the course of the experiment. The arena is 1 x 1 m and there are 5 robots trying to reach the white cylinders representing the events. The simulation runs until 15 events have been handled and displays some simple statistics. Run the simulation a couple of times and at the end of each simulation, take note of the statistics printed in the console which give insight to the time-to-completion and percent of average active time. All robots always decide to stop and move at the same moment. Why?

2.1.2 Impact of threshold

3. **(S)** In the supervisor controller (`threshold_super.c`) there is a parameter named `THRESHOLD`. This parameter is already set to value 2. What does this mean? Re-run the simulation and set this parameter to different values (e.g., 8 and 1). How does this parameter impact the behavior of robots? Why?

2.1.3 Random threshold

4. **(S)** Make the necessary changes in the code and repeat the same scenario with **fixed heterogeneously distributed thresholds** and **global stimulus** announcement. Now, the agents are assigned thresholds randomly, but they continue to use the same value unaltered for the entire duration of the experiment. Again, note what happens, and compare it to the previous simulation.

5. **(B) Briefly** state a few of the drawbacks you see in these two approaches, given that we are working on the problem of efficient *task allocation*; that is, we want to get as much as possible done as quickly as possible with as little 'effort' (resource expenditure) as possible. *(Hint: When does each agent activate? Is the work distributed fairly among the agents?)*

2.1.4 Noisy perception of the stimulus

Now consider a different method for stimulus calculation, similar to that used by Agassounon & Martinoli [1]; each agent must estimate locally (independently) what they believe the stimulus to be based only on the information that they have available to them.

6. **(S)** Run the simulation with **fixed homogeneously distributed thresholds** and **local stimulus estimation**. Set the value of the `THRESHOLD` back to 2. Here, instead of receiving the number of unhandled events from a supervisor, robots are only able to count the events near them (within a certain detection radius). Again, notice what happens in comparison to the previous cases. Pay attention to the function `nearby_events` in the supervisor code.

7. **(Q)** Which of the previous 2 cases (i.e. question 2 and question 4) is more similar to this one? Is this what you expected? Explain why. *(Hint: If you're confused, check [1] or the lecture slides.)*

2.1.5 Impact of sensing range

8. **(B)** In the supervisor controller `threshold_super.c` there is a parameter named `SENSOR_RANGE` which is defined to be 0.25. Read the code and find out what this parameter is. Re-run the simulation a few times and set `SENSOR_RANGE` to different values (e.g., 1.0 and 0.1). What happens? Why?

2.2 Fixed vs. Adaptive Thresholds / Adaptation Rules

As you may have guessed while working with the previous simulations, depending on the particular situation being considered, a certain choice of threshold value(s) may yield better performance, faster completion/convergence, or a fair/unfair distribution of the workload. But what if we do not know a priori all the necessary details for determining the "best" values, or if we prefer the controller to be flexible, portable, or more broadly applicable? Perhaps we can modify it slightly, so as to endow it with the capability to adapt to the environment with which it is presented.

Of course, there are entire laboratories devoted to the study and design of learning algorithms (any of which could certainly be used here), but that is not our primary focus right now, so try to stick with simple arithmetic functions, such as addition, multiplication, exponents, etc. Also, note that in this particular example we are considering a single task and a single "caste" of agents. During the lecture you have seen how threshold-adaptation rules can be used to generate specialization in different tasks amongst different "castes" of agents. However, here we are only concerned with adapting a single threshold in order to improve the global performance.

9. **(Q)** Here are a few pairs of equations for simple threshold-adaptation rules, considering the conditions which cause them to be executed:

1. $\theta = \begin{cases} \theta + k, & condition\ A \\ \theta - k, & condition\ B \end{cases}$

2. $\theta = \begin{cases} (1 + k_1) \times \theta, & condition\ A \\ (1 - k_2) \times \theta, & condition\ B \end{cases}$

3. $\theta = \begin{cases} \theta^{(1+k_1)}, & condition\ A \\ \theta^{(1-k_2)}, & condition\ B \end{cases} \qquad for\ theta > 1$

With k, k1 and k2 positive constants.

Explain how each one of these equations may change the threshold based on two conditions:

What happens when condition A is true? What happens if B is true? What do conditions A & B correspond to?

10. **(I)** Select one of the exemplar rulesets above which you feel is the most promising, and write the bodies of the two functions in `thresholds_adapt.c`:

`adapt_threshold_on_event()` (called after an event is handled)

`adapt_threshold_on_no_event()` (called when no event is handled)

Note: as the `no_event` version is called quite frequently, you will want it to make a very small change (e.g., by k = 0.001). Don't forget to change `ADAPTIVE` to 1 in `thresholds_super.c`.

11. **(S)** Run a few simulations with your adaptation rule, and note its (quantitative) performance, once with local and another time with global stimulus.
12. **(Q)** How does it compare to the non-adaptive version? How is the performance similar to or different from your expectations?

3 Market-based Task Allocation Algorithms

Market-based approaches are based on economic principles of supply and demand. In market-based multi-robot systems, robots are designed as **self-interested agents** that operate in a virtual economy. Both the **tasks** that must be completed and the available **resources** have quantitative value, and can be traded. In this way, tasks can be assigned to robots via market mechanisms—such as an **auction**. When a robot completes a task, it receives "payment" (of virtual currency) for providing a service to the team. However, the robot must also *pay* for the value of the resources it consumed in completing the task. The essence of market-based approaches is that, in a well-designed system, the process of robots trading tasks and resources with one another to maximize individual profit simultaneously increases the performance of the team as a whole.

To illustrate this more concretely, consider a team of robots performing a distributed sensing mission on Mars. Suppose the robots must gather data from specific sites of interest to scientists while consuming the least amount of energy. One important aspect of completing the mission is to determine which robot should visit which site. We can solve this problem with a market-based approach in which robots compete in auctions for the job of visiting a site; the robot with the best bid is awarded a contract for the task. Bids typically correspond to the estimated costs a robot will incur based on the resources it expects to consume to complete the task.

So suppose we offer a maximum reward of $50 and, since the resource of concern is the consumed energy, robots incur a cost of $2 for each meter of travel. This $50 defines a *reserve price* that essentially says that the task should only be attempted if the site can be reached by some path of length less than 25 meters. Furthermore suppose that a robot *A* is only 5 meters from a site S; since *A* would have to spend $10 to complete the task, it bids $12, which includes a 20% mark-up of its cost that it will keep as profit. Meanwhile, a robot *B* that is 10 meters from the site would have to spend $20 so it will bid $24. *A* is awarded the contract because it can perform the task most efficiently and for less than the reserve price.

There are a few main components in a market-based approach:

1. A **global objective (utility) function** that we use to measure the quality of a task allocation. In our example, this objective was to minimize the total energy consumed by the team.
2. A **local objective (utility) function** specified for each robot that quantifies the costs and profits of its activities. In our example, this objective function is the robot's profit: task reward - $2/meter use of energy.
3. A **mapping** between the global objective function and the local objective function that determines how individual activities contribute to the overall solution. In our example, the sum of the individual energy consumption.
4. A **market mechanism** that we use to redistribute tasks. Here, we used an auction.

3.1 The Market: Trade-goods and Objective Functions

Consider the following multi-robot problem: there are a set of hazardous spills sites scattered in a nuclear power plant that need to be cleaned up. Each spill must be cleaned by exactly one robot, and spills require different amounts of time to be cleaned up. We want to distribute these spill sites to the robots so that we minimize the time taken to clean the spills.

13. **(Q)** What are some commodities (things being bought & sold) in this auctioning setup? What are the robots trading? *(Hint: there are two main ones.)*

For the next two questions, you may use the following type of notation:

Distance(r_i, s_j) the distance between a robot and a spill site

TaskList(r_i) the list of spills a robot currently plans on managing

T_i the time at which the cleaning of spill i is completed.

You may use whatever information you need, but please explain it. And remember that for the local objective function, it must be feasible for the robot to have access to the information you use in the function.

14. (Q) "Minimizing the time taken to clean all the spills" (our *global objective function*) can mean a number of different things. Describe two ways we can interpret this goal. Express them as simple equations using T_i.

15. (Q) Write an equation for the *local objective function* used on the individual robots (e.g., what a robot r_i bids to cleanup site s_j). Assume that each robot has complete and correct information about itself and about the spills (e.g., their locations and whether they are finished or not) but no information about its teammates.

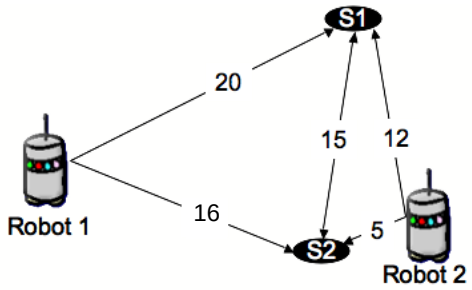
3.2 Experimenting with different auction and bidding strategies

The simulation experiments for this portion of the lab use the files `Market/webots/controllers/auct_super/auct_super.cc` and `…/epuck_crown/epuck_crown.c` which can be compiled to run in Webots (as with the threshold simulations).

These questions will require you to change the bidding function in the file `epuck_crown.c`, in the function `receive_updates()` and **nothing needs to be changed in the other files**. Details about the working of the algorithm can be found in the comments contained in the code.

Essentially, there is a list of events that must be assigned to the robots. The central auctioneer requests one bid from each of the robots and, based on these bids, assigns an event to a robot. In the default setup provided, robots construct tours of events incrementally; that is, a robot only considers adding an event to the end of its task list (there is no mechanism provided for changing the portion of the schedule which has already been assigned to a robot).

16. **(S)** Open the world file `market.wbt` in Webots and run the simulation several times as it is, taking note of the performance. Note that there are 10 robots in this setup, but only 5 of them initially work. You can change the value of results in `NUM_ROBOTS` (in the supervisor and also in the robot's controller) to have up to 10 robots functional. *(Hint: if you regenerate the Makefile, you will have to uncomment line 59 of the makefile: USE_C_API = true)*
17. **(S)** Currently, there is a rather simple default bidding strategy implemented. We implemented a slightly better one for you (commented-out in the function `receive_updates()` under `///*** BETTER TACTIC ***///`) – uncomment this code (comment the simple tactic), recompile and run the simulation. Why is this a better strategy?
18. **(Q)** Quantitatively compare the performances of the provided and improved bidding strategies. You might have the simulation several times to see a tendency, as events are randomly positioned.
19. **(Q)** Consider the setup below, using the slightly modified bidding strategy from the question 17 (`BETTER TACTIC`). We have two robots and two spill sites and the distances between them are shown (not to scale). By inspection, what is the optimal assignment considering the total traveled distance? Now, suppose that we auction S1 and then S2. What is the resulting solution? Explain this problem and give an auction strategy that will solve it. *(Hint: notice that the Bid specifies which Event is being bid on.)*



20. **(I)** Open the world file `market_simple.wbt` where you can find the same simple scenario in Webots. Implement your new auction strategy in the controller code in such a way that the robots behave the way you expected. (*Hint: Read and follow the directions provided under the line with ///*** BEST TACTIC ***/// .*
    Hint: if you regenerate the Makefile, you will have to uncomment line 59 of the makefile: USE_C_API = true)
21. **(S)** Evaluate your newly implemented strategy in the world file `market.wbt` and compare the results with the previous tactic.

3.3 Heterogeneity in market-based systems

Now consider a slightly more complex problem. We again have the hazardous spills domain. However, this time spills are either of chemical A or of chemical B. Again, we are interested in minimizing the time taken to handle spills.

22. (B) Suppose that we also have two types of robots. A-robots can only handle A-spills, and B-robots can only handle B-spills. Will we have to change the global objective function, and if so, how? Will we have to change the local objective function, and if so, how?

23. (B) Suppose that we have A-Robots and B-Robots again, but now A-robots are better (e.g., faster) at A-spills than B-spills, and the opposite is true for B-robots. Will we have to change the global objective function and, if so, how? Will we have to change the local objective function from the previous question and, if so, how?

4 Comparing market-based and threshold-based approaches for task allocation

24. (B) For what types of scenarios are market-based approaches most well suited? What about for threshold-based approaches? Consider the task information available to the team, the (different) physical capabilities of the team members, availability of communication and/or computational power, and the requirements/measures of success. Try to come up with a couple of general indicators that would cause you to select one over the other.

25. (B) Consider the following scenario: You have been hired to modernize a production line by using a fleet of mobile robotic agents. The production flow is defined by a series of interdependent tasks (the output of one task serves as input for the next). The robots are generalists capable of handling any of the tasks by switching among their tools (with a certain time penalty). Which of the two division of labor methods presented in this lab would you implement to obtain a system that is adaptive to variations in the raw material supply and robust to robot brake-down? Justify your choice and explain the fundamental elements (e.g., stimulus, threshold for threshold-based, and commodities, local/global objective functions for market-based) of the respective method in the presented context.

5 References

[1] Agassounon W. and Martinoli A., “Efficiency and Robustness of Threshold-Based Distributed Allocation Algorithms in Multi-Agent Systems”. Proc. of the First Int. Joint Conf. on Autonomous Agents and Multi-Agent Systems, July 2002, Bologna, Italy, pp. 1090-1097.