

FULL PAPER

The effect of learning by imitation on a multi-robot system based on the coupling of low-level imitation strategy and online learning for cognitive map building

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It is assumed that future robots must coexist with human beings and behave as their companions. Consequently, the complexities of their tasks would increase. To cope with these complexities, scientists are inclined to adopt the anatomical functions of the brain for the mapping and the navigation in the feld of robotics. While admitting the continuous works in improving the brain models and the cognitive mapping for robots' navigation, we show, in this paper, that learning by imitation leads to a positive effect not only in human behavior but also in the behavior of a multi-robot system. We present the interest of low-level imitation strategy at individual and social levels in the case of robots. Particularly, we show that adding a simple imitation capability to the brain model for building a cognitive map improves the ability of individual cognitive map building and boosts sharing information in an unknown environment. Taking into account the notion of imitative behavior, we also show that the individual discoveries (i.e. goals) could have an effect at the social level and therefore inducing the learning of new behaviors at the individual level. To analyze and validate our hypothesis, a series of experiments has been performed with and without a low-level imitation strategy in the multi-robot system.

Keywords: learning by imitation; imitation; bio-inspired architecture; cognitive map; multi-robot system

1. Introduction

In an unknown environment, interactions among robots can be based on stigmergy [1] which refects indirect communication through the environmental changes. To share partial knowledge of this environment in a multi-robot system, several benefits can be expected from the imitation capability.[2–6] The imitation strategy can be considered as a powerful tool for autonomous robots based on a bioinspired architecture to learn and discover new tasks and places. We believe that it is a step forward in bio-inspired architectures (for the navigating robots) by introducing imitation. For instance, RatSLAM algorithm designed by [7] is a bio-inspired simultaneous localization and mapping (SLAM) system based on computational models of rat's hippocampus or BatSLAM [8] (inspired by Bat's navigation system), both algorithms provide the way to navigation and mapping, and we come up with the idea on how to accelerate this mapping process by associating hippocampus navigation with imitation strategy.

Modern robotics considers imitation as a powerful behavior that enables learning by observation or imitation [9-15] even if the imitation was not intentional (i.e. imitation emerges from the ambiguity of perception in a simple

sensori-motor system).[2] The idea of learning by imitation for robots is inspired by the notion of imitation described by developmental psychologists. According to psychologists, [16] immediate or low-level imitation corresponds to the ability of a child (few months old) to imitate (spontaneously) meaningless gestures. This low-level imitation may serve to higher level functions. It is not only the tool for learning but also a way to communicate and to accelerate the learning process. To highlight the role of the imitation, we started with an experiment (see Figure 1) which describes the success of interaction between a human and a robot.

The goal of this experiment was to allow a robot to follow/imitate the human's trajectory to discover the positions of the goals in the environment. Indeed, Figure 1 from (a) to (l) shows the discovery of the f rst and the second goals (G1 and G2) based on the imitation capabilities. The arrows in Figure (e) and (l) show the trajectories of the robot. At this level, the question is to know what would happen if we replace the human by a robot? In this paper, we study the effect of learning by imitation in a multi-robot system which is based on the cognitive map ¹ for navigating and planning. Particularly, we analyze the association of the concept of a very low-level imitation, with our bio-inspired

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Figure 1. The success of the human–robot interaction based on imitation capabilities. With the following of the trajectory of the human, Figure (a)–(e) show the robot's success to discover the f rst goal (G1) and Figure (f), (i)–(l) show the success in the discovery of the second goal (G2). The video is available at http://persoetis.ensea.fr/neurocyber/Videos/Cognitive_Multi-Robot_System/Interaction_Human_Robot.

architecture which allows the learning and the building of the cognitive map.

This paper is organized as follows: in Section 2, the theory and the bio-inspired architecture of our proposed cognitive

map are presented. Section 3 analyzes the impact of the cognitive map's adaptation in the context of a multi-robot system. Section 4 describes the neuronal architecture for the imitation process. Section 5 details experimental results and

f nally, before concluding, Section 6 examines the positive feedback of imitation strategy in a cognitive multi-robot system.

2. A bio-inspired architecture for cognitive map building

Starting from neurobiological hypothesis which highlights the importance of the hippocampus in the spatial navigation, [17] form a model of the cognitive map in the hippocampus representing the entire environment and suggest the shortest paths to a given goal. The model proposed by [18] provides a complete neural architecture of the learning process. The model uses a cognitive map and associates it with a mechanism of action selection.[19,20] Also propose a model of cognitive embedded in a parieto-frontal network, which is based on cortical columns. Based on the same research, different authors [21-24] have disclosed special cells in the rodent's hippocampus that f re when the animal is at a precise location. These neurons are called place cells (PC). We do not directly use them to navigate, plan, or construct a map, we rather use neurons called transition cells (TC).[25] A transition cell codes a spatio-temporal transition between two PCs that successively win the competition at time t and $t + \delta t$, respectively. The set of the PCs and the TCs constitute a non-Cartesian cognitive map. The reason behind using TC is that their association with an action is univocal and quite straightforward. Thus, there is no need for an external algorithm to extract the action from the cognitive map.

Our architecture takes inspiration from the model presented in [26] which describes the role of the hippocampus. Indeed, the entorhinal cortex which is the main input to the hippocampus (EC) receives signals from associative cortical areas then flters and merges this multi-modal information in order to transfer it to CA3 pyramidal cells and the dentate gyrus (DG). The DG puts the signals together in a temporal hierarchy which later on is re-transmitted to CA3 cells. This temporal hierarchy allows CA3 to be aware of past events and put them in correspondence with present events, therefore the temporal hierarchy behaves like an associative memory through stocking possible transitions between these events. The recognition of the ongoing sequence happens at the level of CA1 using EC and CA3 information. It also extends to the prefrontal cortex (PFC) to serve higher levels of cognitive processes.

To create the PC, the robot takes a visual panorama of the surrounding environment. A camera mounted on a pan system allows to perceive the environment or the surroundings. The visual images are processed to extract visual landmarks. These landmarks are learned and a visual code is created by combining the landmarks and their corresponding azimuth. This conf guration serves as a code for PCs. The signals provided by the EC are solely spatial and consistent with spatial cells' activities. In order to select (only) the cell with the strongest response at a specific location, spatial cells' activities are submitted to a winner-take-all competition. We subsequently speak about the current location by indicating the spatial cell which have the highest level of activity at a given location. The temporal function at the level of the DG is reduced to the mere memorization of the past location. The acquired association at the level of the CA3 pyramidal cells is then the transition from a location to another besides all information concerning the time spent to carry out this transition. Once the association from the past location and the new one is learned, every new entry will reactivate the corresponding memory in the DG. A schematic view of our architecture is shown in Figure 2.

During the discovery of the environment, the cognitive map is gradually created when the robot moves from one place to another. It is possible that multiple PCs (previously learned) are similar to the current location perceived according to the f xed value of threshold of vigilance. To select a single PC having the strongest response to a specif c location, the activities of spatial cells are subjected to a competition called winner-take-all. It allows the identif cation of the current location by the spatial cell having the highest activity at a given location. The winning activated PC indicates the recognition of this place which is already visited. If none of the PC activates, the current location is considered as an unknown location and this location is learned by another PC and it will be activated on revisit the same location. The equations which govern the learning process in the cognitive map are given below as Equations (1) and (2):

$$\frac{dW_{ij}^{CC}(t)}{dt} = T(t). \begin{array}{c} ! & " \\ (\gamma - W_{ij}^{CC} & X_i^C(t) X_j^C(t) \\ ! & . \\ - W_{ij}^{CC}(t) & \lambda 1 X_j^C(t) - \lambda 2 \end{array}$$
(1)

$$\frac{dW_{ij}^{MC}(t)}{dt} = S(t) \quad \text{for}_{i,j} = arg_max_{k,l} \quad X_l^C(t).X_M^K(t) \quad (2)$$

T(t) is a binary signal (0 or 1) activated when a transition occurs (moving from one place to another). This signal controls the learning of recurrent connections on the cortical map W^{CC} . γ is a parameter less than 1 which regulates the distribution of motivation activity on the map. λ 1 and λ 2 are, respectively, parameters of active and passive forgetting. S(t) is a signal associated with the goal satisfaction. This signal controls the learning of synaptic connections between neurons in W^{MC} motivations' activity X^M and neurons of the cognitive map of activity X^C . After having explored the environment, the robots are in a position of predicting the locations directly reachable in each situation and to perform a gradient ascent according to their cognitive maps and their associated drives.



Figure 2. From the construction of the visual code of PC to the creation of the cognitive map.



Figure 3. Simplified view of the cognitive maps of the robots based on TC. Figure (a) presents an unknown environment with a size of x = 3.82 m and y = 4 m. Figure (b) and (c) present, respectively, the cognitive map of the first and the second robot. The construction process is based on place recognition using PCs, activation of one PC and delayed activation of another and allows for transition prediction (green transition) and the need for goals (G1 and G2) triggers maximum motivation for a given goals. The video is available at http://perso-etis.ensea.fr/neurocyber/Videos/Cognitive_Multi-Robot_System/CMRS.

3. The adaptation capabilities of the cognitive map

In order to show the robustness of this architecture, we tried to study initially the behavior of a cognitive multi-robot system capable of learning several goals in an unknown environment. Figure 3(a) presents the initial unknown environment with its size of x = 3.82 m and y = 4 m. The environment is composed of two goals (G1 and G2), two obstacles (O1 and O2), and two identical robots (the robots were equipped by the same tools) with an experiment time frame equal to 30 min and a threshold of vigilance equal to 0.65. The threshold of vigilance (which has a value between 0 and 1) is a variable that controls the learning rate of the neuronal network and in our case also controls the density of PC on the cognitive map. In practice, a new place cell is recruited when the winner cell activity is lower than the vigilance threshold. Thus, when the threshold of vigilance values is high, the robot learns more PC.

Figure 3 shows that our cognitive robots are able to avoid the stable and dynamic obstacles, to navigate, learn, and construct their own cognitive map online (at the same time) in a unknown environment. The shape of the cognitive map in Figure 3(b) or (c) proves that map construction is well related to the robot's own perception: the different robots learn the environment and the position of the two goals in a different manner, and the number of the PCs is not the same (7 for the f rst robot, and 9 for the second robot with the same threshold of vigilance).

3.1. Robustness to environment changes

In the previous part, the robots were able to construct their own cognitive map which allows them to navigate and to plan their path in f nding goals. To analyze the evolution of the cognitive map, we kept the following parameters unchanged: cognitive map for each robot, the threshold of vigilance, and the duration of the experiment like in the previous experience. Now, we change the structure of environment by increasing its size (x = 3.82 m and y =7 m) and by changing the positions of the obstacles (see Figure 4(a)).



Figure 4. The adaptive capability of the cognitive map induced by a changing environment where its new size is x = 3.82 m and y = 7 m and G1 and G2 are the goals. Figure (a) and (b) presents, respectively, the evolution of the cognitive map for the f rst and the second robot.



Figure 5. The components of the RR and the cognitive robot.

Figure 4(b) and (c) shows that, taking into account the new modif cations in the environment, both robots were able to continue to adapt their own old cognitive maps while learning the new environment through adding new PCs and TCs. Thus, the changes of the environment did not disturb the robots in their continuous learning of the new environment. This validates the robustness of the cognitive map and capacities to associate and dissociates drives with specif c TC on the cognitive map.

4. The neuronal architecture for the imitation process

In order to share a partial knowledge of the environment, direct communication between robots could be used. However, it implies the capability to build some abstract representation of the world which is not present in our model. The presented architecture is based on the stigmergy to communicate between robots. Thus, imitation seems like an interesting way to strengthen this architecture. We describe here a very simple architecture for imitation in a navigation perspective. The proposed model is based on dynamical interactions among mobile robots. Let's start by showing the components of the reactive robot (RR) and the cognitive robot that we used in our experiments (see Figure 5). It's important to note that to avoid obstacles we used a Braitenberg mechanism. Indeed, our robots are equipped with IR sensors for the detection and avoidance of obstacles. They see obstacles with f ve binary sensory inputs associated with f ve sensors (left, front left, front, right front, and right). Robots are then able to know if they are about to face obstacles with a rough indication of their directions.

Our aim is providing limited capabilities to a mobile robot to interact dynamically with other robots by following their current direction of movement. Figure 6 shows the architecture of our imitation model. As shown in



Figure 6. The architecture of our imitation model. Figure (c) shows the neuronal architecture to imitate or follow the other robots depending on the estimation of their velocity vectors (optical f ow). Figure (a) presents the optical f ow function shown by our neuronal simulator Prometh when the two robots move at the front of the imitator robot. The +ve and the -ve are the apparent visual speed in pixel/s. The +ve (move left) and -ve (move right) activities are shown, respectively, by black blocks and blue blocks. The intensity or strength of blocks ref ects the speed of the respective moving object. Figure (b) describes how an imitator robot perceives the movements of the other robots. We added the arrows to show the motion direction of two robots (presented by the right and left arrows) detected by the robot taking the image.

Figure 6(c), perceived motions (by a camera) in the visual f eld of the robot are estimated by a classical optical f ow algorithm.[27] If the perceived motion is in the upward direction, it is considered as a positive activity. On the other hand, downward motion is accumulated as negative activity. Similarly, motion on the left direction leads to negative activity while movements on the right direction are considered as a positive activity. Figure 6(a) and (b)shows the snapshots taken during the experiment illustrating optical f ow functioning. There are two moving objects in the optical feld of the robot. One moves left to right and that is transformed into negative activity by the optical f ow (shown by blue blocks) while the other moves right to left and that is transformed into positive activity (shown by black blocks). To determine the correct motion direction in following an interacting partner, optical f ow activities are transferred to a short-term memory block, this block is used to avoid the fast changes in the environment. Then, all the pixels of short-term memory module are projected on the x-axis (i.e. all pixels in each column are added). Winnertakes-all (WTA) selects the highest activated column. This selected column indicates the direction of the movement and the robot can point and follow the interactor.

For this experiment, the resolution of the image is 32×24 (32 columns or location), these 32 possible locations are realized in 60° (-30° to 30°) circular angles which are fed to the motor according to the corresponding columns (column zero refers to -30° while 32th column corresponds to 30°) and 0° when the agent stands in front of a mobile robot. If two or more visual stimuli are presented at the same time then our proposed imitation algorithm dynamically

locates and selects the interacting agent whose estimated velocity vectors are the highest.

5. The positive effect of imitation in the behavior of a multi-robot system

In this part, we try to study the feasibility of our experiments in the multi-robot system. Indeed, we try to show, through two experiments, the positive feedback of the imitation which allows the imitator robot to discover both goals. The f rst experiment is done with a simple RR which only has an imitation capability. The second one is done with a cognitive robot which has an imitation capability along with the ability to create its own cognitive map. It is also important to mention that in these experiments the imitated robot is never aware of being imitated.

5.1. Imitation performed by a reactive imitator robot

To study the inf uence of imitation on the behavior of the robots, we added two cognitive robots ² along with one RR which uses just an imitation strategy. Figure 7 shows at t0, the RR tries to follow one of the two cognitive robots (CR1 and CR2) which are in navigation tasks. Indeed, at t1, the RR detects CR1 and imitates it in its current direction of motion consequently achieving the f rst goal at time t2. At t3, t4, t5, and t6, the imitation strategy allows the RR to f nd the second goal with the help of CR2. It is important to note that CR1 and CR2 are faster than the RR. For this reason, at t2, we see that CR1 changes its direction and moves while RR still searches for the goals. Moreover,



Figure 7. The inf uence of the imitation behavior in the multi-robot system. The experiment is done with three robots. RR is the reactive robot; CR1 and CR2 are the cognitive robots; and G1 and G2 are the two goals. The Figure is presented with chronological order. The trajectories of the robot show that RR is able to f nd the two goals by imitating the trajectories of CR1 and CR2. In the trajectories of robots, the normal lines show the two cognitive robots' trajectories when using their cognitive map. The bold lines show the trajectories of the imitator RR. Indeed, for each step we noted the number of the followed robot (imitation of CR1 or CR2). The red dashed lines show when the cognitive robots CR1 and CR2 were imitated by the RR. The video is available at http://perso-etis.ensea.fr/neurocyber/Videos/Cognitive_Multi-Robot_System/Imitation_CRs-RR.

at t6, when the RR f nds the second goal, the CR2 is already far from the RR. The trajectories of robots demonstrated in Figure 7 allow to further explain the individual behavior of each robot in more details. Indeed, the normal lines show the two cognitive robots' trajectories when using their cognitive map, the bold lines show the trajectories of the imitator RR, and the red dashed lines show when the cognitive robots CR1 and CR2 were imitated by the RR.

5.2. Imitation performed by a cognitive robot

After the discovery of the two goals by the RR through the help of the cognitive robot, the RR is not able to return to the goals on his own again while depending on its needs because it didn't learn their positions in the environment. The proposal is to combine the imitation strategy with the creation of the cognitive map. Thus, the cognitive imitator robot could create its own cognitive map during the imitation. Once it discovers both goals, it stops the imitation strategy and then it can satisfy its needs by using its cognitive map. For the sake of simplif cation, we use a minimal setup (see Figure 8). It includes two goals, three obstacles, and two robots: leader robot LR (which has already learned the environment and the positions of both goals G1 and G2) and the imitative cognitive robot IR (which is capable of imitating and following the other cognitive robot LR and of creating its cognitive map online).

Figure 8(a), (b), (d), and (e) shows that the *IR* tries to construct its own cognitive map by following the cognitive robot *LR* (when *LR* navigates towards the goals using its own cognitive map). Figure 8(c) and (f) demonstrates that the *IR* has succeeded in discovering both goals *G*2 and *G*1 during the imitation process or by following the *LR*. Throughout the experiments, it was notable that the *IR* also has the capability of learning and of constructing its own cognitive map (online) independently, but if the same task is performed by using imitation tactic it boosts the performance (as a function of time) of discovering goals and creating a cognitive map. After discovering the positions of both goals, the *IR* will be able to return alone to the both



Figure 8. The inf uence of the imitation behavior in a multi-robot system. The experiment is done with two robots: *IR* imitator cognitive robot and a simple cognitive robot *LR* that have already learnt the environment and the position of the goals G1 and G2. The Figure is presented with chronological order and proves that the imitator robot was able to f nd, learn the two goals G1 and G2, and create its own cognitive map. Thus, it can satisfy its needs on its own by using its cognitive map. The video is available at http://perso-etis.ensea.fr/ neurocyber/Videos/Cognitive_Multi-Robot_System/Imitation_LR-IR.mov.

goals using its own cognitive map. This experiment proves the importance of imitation in multi-robot system.

To further understand the robots behaviors, Figure 9 demonstrates the trajectories and the individual behavior of robots in more details. The arrows are the initial positios of the two robots in the environment.

The dashed line traces the trajectory of IR whereas trajectory of LR is shown by the continuous line. IR's trajectory shows that the robot tries to go to the position of LR when IR detects it in its visual f eld. It is evident that when IR is close to the LR, its trajectory tries to follow the trajectory of LR (the two trajectories are confounded). The trajectories of the robots show that IR is able to f nd the two goals G1 and G2 by imitating the trajectory of LR. It is noticeable that the robots do not have localization tools. Thus, we used the robots odometries in order to plot their relative locations and their trajectory is plotted after 4s which is presented by one wheels' tower.

6. Analysis of the effect of learning by imitation

In order to evaluate the effect of learning by imitation in the multi-robot system, we introduced (i) the goal discovery time (time taken by a robot to discover both goals) and (ii) the number of the PCs. These parameters could characterize the performance of our system.



Figure 9. The trajectories of robots to reach the goals. The cognitive map allows the LR to f nd the two goals. Thanks to the imitation strategy, the IR is able to f nd goals when it follows the trajectory of the LR. The IR has the capability to learn the environment and the positions of the goals through creating its own cognitive map. Thus, after the f rst discovery of the two goals, the IR is able to return alone to the goals. Figure (a) and (b) show, respectively, the discovery of the goals G1 and G2.



Figure 10. The average time of the goals' discovery. The f rst curve (from the left) shows the time to discover the goals by an imitator cognitive robot (with imitation capability) along with a leader cognitive robot which already knows the goals. The second curve (dotted line) describes the time taken by a RR (without imitation capability) to explore the goals along the same leader cognitive robot as in the previous case. The last curve demonstrates the average time needed to f nd the goals when a single RR explores the environment randomly.

Table 1. Fisher tests in f nding the average time of the goals discovery time.

Scenarios	Total tests	Fisher value	Test taken for Fisher value
Reactive robot	16	5.387	8
Reactive robot with cognitive robot	16	15.792	16
Imitator cognitive robot with cognitive robot	16	2.153	8

6.1. The effect of imitation on the goal discovery time

In order to compute the discovering time of both goals in the environment, three different experiments have been tested according to the following scenarios: (i) a single RR in the environment without imitation capability, (ii) the same RR without imitation capability along with a robot that already knows the locations of the goals, and f nally (iii) a cognitive imitative robot along with a leader robot that already knows the locations of the goals in the environment.

To f nd the average time for the goal's discovery in each scenario, we conducted several tests with the change of the robot's starting position and also the location of goals. The number of tests to take the average value is determined by the Fisher exact test. It is a statistical test that compares the difference between two variances of two sets of tests (having the same number of observations) by taking the ratio between them according to Equation (3):

$$F = S_x^2 / S_v^2 \tag{3}$$

where S_x^2 and S_y^2 are the variances of two sets of tests. S_x^2 is the numerator and it always has the larger value between two variances. If the ratio (*F*) does not exceed a certain theoretical value (available in the table of Fisher), it can be accepted. On the other hand, if *F* is greater than the theoretical value, we reject the hypothesis of equality of two variances, in this case we increase the number of experiments to close the theoretical value of equality of two variances.

For the first scenario, where a RR (without imitation) looks for goals, we conducted two sets of tests (four tests in each set) and computed the Fisher value (F = 5.387), it is less than 19 which is given in the table of f sher. For the second scenario, where the same RR explores the environment along with a cognitive robot, we conducted two sets of tests (four tests in each set) and computed the Fisher value (F > 100), it is greater than 19 and unacceptable. To reduce the difference in variance, we conducted another set of tests (4 tests in each set) and computed F = 15.79, it is less than 19 (does not exceed Fisher's theoretical value). Finally, for the last scenario, where the imitative cognitive robot imitates the leader cognitive robot to f nd the goals, we applied two sets of tests (4 tests in each set) and calculated the Fisher value (F = 2.153), it is less than the theoretical value (19). To have a better comparison, we summarize the results of the Fisher tests by the Table 1:

The average time in f nding the two goals for each scenario is plotted in Figure 10. Thanks to the learning by imitation strategy, the imitative cognitive robot, which is part of the third scenario, takes less time to f nd both goals (G1 and G2), its accumulative average time is about 5



Figure 11. The inf uence of the imitation on the creation of the cognitive map of an imitator cognitive robot. (a) Shows the cognitive map of the *LR* which already learned the environment and the positions of both goals G1 and G2. (b) Shows the cognitive map of *IR* that is created after applying the imitation strategy. (c) Presents the two cognitive maps in the same plan. The f gure proves the positive effects of the imitation strategy which allows the *IR* to f nd the two goals and to create its own cognitive map where its shape is more simple than the *LR* 's cognitive map.



(a) Robot like an obstacle (b) Not Interesting Imitation (c) Accessibilities Problems



min (2 min for G1 and 3 min for G2). Once the imitator cognitive robot discovers both goals, its own cognitive map allows it to plan to the goals' locations. Thus, the imitator cognitive robot is able to better optimize its goals' discovery time (less than 5 min). However, the RR of the f rst and second scenarios takes much more time (about three times more) to discover goals. Indeed, for the f rst scenario, the accumulative average time is 22 min (6 min for G1 and 16 min for G2); similarly, the second scenario takes 19 min (6 min for G1 and 13 min for G2).

The results of the f rst and the second scenario shown in Figure 10 allow us to analyze the inf uence of the presence of multi-robot in the same environment. The difference between these scenarios is the way of exploring and accessing the goals. Indeed, in the f rst scenario, the RR discovers

the goals without any diff culty of accessibility. However, in the second scenario, it is not easy to discover them because the cognitive robot (which has already learned the goals' position) acts as a dynamical obstacle. It means that the RR could lose or win its discovery time. Indeed, when both robots are close to the goal, the RR, instead of heading towards this goal, changes its direction to avoid the dynamical obstacle. However, when both robots are far from the goals, the RR can avoid the dynamical obstacle (the cognitive robot) and f nds easily the goals which are available.

6.2. The effect of imitation on the cognitive map

The cognitive map is a way to describe the complexities of the environment. By adding a simple imitation strategy, we allow the IR to share these complexities and to learn the experience of the LR in order to achieve its goals. Since the IR has the capability of creating its cognitive map, when it follows the trajectory of the LR, its cognitive map will be inf uenced by the LR. Figure 11(a) and (b) shows the cognitive map of the LR and the IR, respectively. In order to see the difference between the two cognitive maps, we put them in the same plan (see Figure 11(c)).

It is noticeable that there is a similarity between the two cognitive maps at the level of the PCs, TCs, and the shape of the cognitive maps. This similarity shows the positive effects and the success of the imitation process which allows the IR to follow the LR and to discover and learn both goals. As a quantitative measurement, we can analyze the number of the PCs and the TCs. Indeed, we noted that the shape of the *IR*'s cognitive map is more simple than the shape of the LR's cognitive map. Thus, the learning by imitation allowed the IR to optimize its number of PCs (from 12 of LR's PCs to 8 PCs) and also to optimize its TCs (from 30 LR's TCs to 19 TCs) with the same ability to reach both goals G1 and G2, in the same environment as the LR. This optimization could better optimize the IR's planning time and its goals' discovery time due to the simplicity of its cognitive map.

6.3. Situations that occurs in the imitation experiments

In the experiments with multi-robot, we noted several situations where the performance of the system decreases regardless of robots used (reactive or cognitive). Figure 12(a) shows that besides the static obstacles, the LR can be a dynamic obstacle in the environment, and instead of following it, the IR has to change its direction to avoid it. Another case appears when the *IR* tries to follow the *LR* without knowing whether the LR goes to the goals or not. In this case, the *IR* may follow the *LR* to f nd uninteresting places (see Figure 12(b)). Finally, we can also have accessibility problem (see Figure 12(c)). It occurs when the robot is unable to satisfy its needs because the goal is occupied by another robot. To resolve these situations, integration of emotional mechanism seems necessary.[28] Indeed, the facial expression could be another way of communication which also respects the conditions of the stigmergy. For instance, adding an expressive head on the LR could allow the IR to know when to start the imitation and when to expect the access of the goals.

7. Conclusion

In this paper, we started by revealing the adaptive capability of the cognitive map based on the brain mapping strategies that enable a multi-robot system to adapt in an unknown environment in order to solve navigation tasks. We suggested a set of experiments in real robots that shows how each robot system is able to learn, adapt, and create online cognitive map and how this architecture allows the robots to learn various goals in an unknown environment. We also highlighted the importance of the imitation strategy which boosts the capability (as a function of time) of a cognitive multi-robot system to adapt to an unknown environment. It also allows to solve the navigation task among various targets. Finally, we proved that combining the learning capability with a simple imitation strategy leads (in a real multirobot system) to a positive feedback both at the individual and the social level. Moreover, it optimizes the time to explore the goals, and it allows the imitator robot IR to create a cognitive map (approximately in the same shape as the Leader robot LR). Thus, to keep the rules of the stigmergy, imitation strategy becomes the way for robots to share knowledge without direct communication. Our architecture which is based on learning by imitation could be used in many areas. For instance, in [29] authors used this architecture to learn trajectories of the robot's arm. Indeed, the model is based on some dynamical equations which provide a motor control when exploring and converging capacities. A visuo-motor map is used to associate positions of the end effector in the visual space with proprioceptive positions of the robotic arm. It enables a fast learning of the visuo-motor associations without needing to embed a priori information. The controller can be used both for accurate control and interaction.

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Notes

- 1. The cognitive map is a graphical representation of the environment which is related to the perception of each robot. It allows the robot to navigate, to plan, and learn the important places in the environment.
- 2. The robots were already learned the position of the two goals and created their cognitive map.

Notes on contributors



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