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“Look out!”: Socially-Mediated Obstacle Avoidance in Collective Transport

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Abstract. In this paper, we present a novel methodology to perform collective transport in the presence of obstacles. Three robots are physically connected in a semicircle around an object to be transported from a start to a goal location.
The task poses two main challenges. First, the presence of both a goal and obstacles requires appropriate negotiation of the direction among the members of the group. Second, since the robots are attached in a semi-circle around the object, they need to maintain a certain orientation of motion in order to maximize the sensor's perception range. We developed two interacting behaviors to tackle these two issues. In the experiments done in simulation, efficiency was analyzed in an environment with only one obstacle, and robustness in an environment with several obstacles.

1 Introduction

In collective transport, a group of robots has to cooperate in order to transport an object. In general, the object is hard or impossible to be transported by a single individual (i.e., because big or heavy), thus making cooperation necessary. The task is even more difficult when communication is limited, there is no access to global information or when using a decentralized approach. In these cases, an effective distributed coordination among robots is necessary.

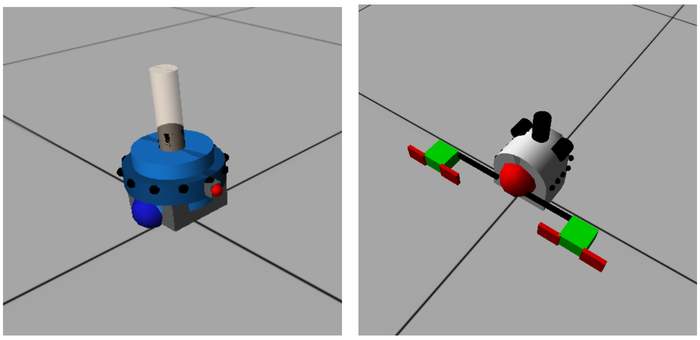
Several works on collective transport were developed using centralized approaches like leader-following behaviors. In these works [1, 2] small robots are able to collectively push/pull an object. In order to coordinate their movement, they follow a leader that has the knowledge of the goal area or of the path.

Donald et al. [3] and Yamada et al. [4] were among the first to study collective transport with limited communication. In the first work, robots had to transport an object without a goal location, whereas in the second work robots had to carry an heavy object towards a common goal determined by a light emitter (photo-taxis).

Campo et al. [5] investigated the use of goal negotiation strategies for performing collective transport to a given goal location. In their work, robots had only a noisy perception of the goal direction, or they were not able to perceive the goal at all. Their robots used LEDs and camera to perceive the orientation of their neighbors, and used it to compute an average direction of motion.

Groß and Dorigo [6] used artificial evolution to synthesize a neural network to achieve collective transport. Their robots were able to cope with different object sizes and weights as well as with different group sizes (from 4 to 16). Groß and Dorigo were able to obtain three different transport strategies. In the first the robot directly connect to the object and pull it. In the second the robots connect to each other (self-assembly) and to the object in order to pull it. In the third strategy the robots created a physical loop around the object. This last strategy involved a high number of robots and a small (but heavy) object.

Trianni et al. [7] studied a task similar to the obstacle avoidance in collective transport tackled in this paper. They call it *collective hole-avoidance*. In their task, robots are physically connected to each other, and they have to navigate in an environment presenting holes and open borders. The authors used artificial evolution for the synthesis of robot's neural network controllers, and studied different communication strategies among the robots: no direct communication, handcrafted signaling and communication induced by artificial evolution. Differently from the work described in this paper, in [7] no object had to be transported. Furthermore, their robots did not have



(a) (b)

Fig. 1: Picture of the simulated foot-bot (a) and of the hand-bot, the irregularly shaped carried object (b).

a specific goal direction on where to go but they were rather exploring the environment while avoiding holes.

In this paper, we study a task which differs from the ones studied in the literature. A group of three simulated robots have to transport an object from a start to a goal location in an environment with obstacles. The robots are physically connected to only a particular region of the carried object (Figure 3a). Almost all tasks studied so far in the literature consider collective transport in an obstacle-free environment where a goal location is given, with the exception of Trianni et al. [7] where instead a goal location is not given but the environment is cluttered. This paper presents, to the best of our knowledge, the first behavior tackling a task where an object has to be carried to a precise location and, at the same time, obstacles are present in the environment.

The remaining of the paper is organized as follows. In Section 2 we describe the task and the simulated robots. In Section 3, we describe the methodology we use to design the controller. In Section 4 we present experimental results, whereas in Section 5 we conclude and sketch possible future works.

2 Task definition

A group of three identical simulated mobile robots (Figure 1a) has to attach to an irregularly shaped object and to collectively transport it from an initial to a goal location. The robots we used are modeled after the foot-bot robot, in development for the Swarmanoid project [1]. The irregularly shaped object is an object which cannot be grasped through its entire perimeter but only in certain regions. In our case, it is another, simulated robot of the Swarmanoid project, the hand-bot (Figure 1b) [8]. This robot is a manipulator that does not have locomotion capabilities and thus needs to be carried by the foot-bots. In this task, the handbot is passive during the entire process.

The environment is an arena where a number of cuboid-shaped obstacles are present, each in a arbitrary positions and orientations. Each of the three simulated mobile robots is equipped with a number of sensors and actuators. We considered and used only the following sensors and actuators: a light sensor, that is able to perceive a noisy light gradient around robot; a distance scanner that is used to obtain noisy distance value from the robot to the closest object [9]; a range and bearing communication system, with which a robot can send a message to other robots that are within its range of sight [10]; a gripper actuator that is used to physically connect to the transported robot considered in this experiment; a turret actuator that is used to rotate the gripper installed on a rotating ring; a wheels actuator that is used to control independently the left and right wheels speed of the robot.

[1] http://www.swarmanoid.org

In the experiments, the light source has a high intensity such that it can be perceived by all the robots. The range of the range and bearing communication device is 4 meters, more than enough to guarantee communication between the robots when connected. The distance scanner has a range of 1.5 meters.

In this task, we rely on the following two assumptions.

Assumption 1: Common environmental clue. A common environmental clue, perceived with the light sensor by all robots, is available. In the experiments, we placed a light source installed in a fixed position in the environment behind the goal area.

Assumption 2: Pre-attached robots at fixed positions. All three robots starts already attached to the robot that will be transported. This can be achieved using techniques such as the one developed by [11]. Furthermore the robots know at which position they are assembled. Any robot can be assembled at the left, center or right with respect to the carried robot (see Figure 3b).

For the sake of simplicity, robots considers as goal direction the direction of the light source, that is they perform photo-taxis. Since the proposed methodology is not restricted to this case, in Section 3 we consider the goal direction and the environmental clue (or light) direction as two separated concepts.

The presence of obstacles and the need to move to a given goal location create the need of handling conflicting individual decisions which can be produced due to the non uniform perception of the environment.

Furthermore, the three carrying robots can only assemble in a semi-circle around the irregular object to be carried (Figure 3b). They use the distance scanner to detect the presence of obstacles. To maximize the possibility of obstacles being detected, we require the carrying robots to continuously face the goal direction (see Figure 3b). This induces an additional constraint on the task: robots have to continuously check if they are *misaligned*, that is, the transported object is not behind the robots (Figure 3b). If the object is misaligned, the robots need to re-align the transported object in order to minimize the chances of an obstacle appearing in an area not covered by robots' sensors.

For each individual robot, information of the following nature can be available at a given time:

No information: The goal direction is not perceivable, for example because occluded by obstacles, or no obstacles are in the range of sight.

Goal only: Only the goal direction is perceivable, hence the robot has to move towards a goal direction while keeping the carried object behind the robots.

Obstacle only: The robot does not perceive the goal direction. However, it perceives the direction of an obstacle, hence it has to avoid it. At the same time, it has to convince the other robots to avoid the obstacle as well.

Goal and obstacle: The robot perceives both the goal direction and the obstacle direction. The direction of movement, considered by the robot and communicated to the other robots, has to take into account both these elements.

We now have all the elements to introduce the methodology used to solve this task.

3 Methodology

In this section we first analyze the main issues raised by the task and we introduce the main idea behind the methodology. Subsequently, we present the controller, which has been decomposed in multiple sub-behaviors. The main two sub-behaviors, that is social mediation and collective transport, are explained in more details in Section 3.1 and Section 3.2.

Section 2 depicted the nature of the information possibly available to each robot at a given time. Different robots in the group can have access to conflicting information, for example one might

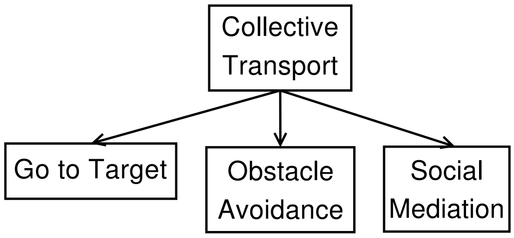


Fig. 2: The decomposition of the collective transport behavior

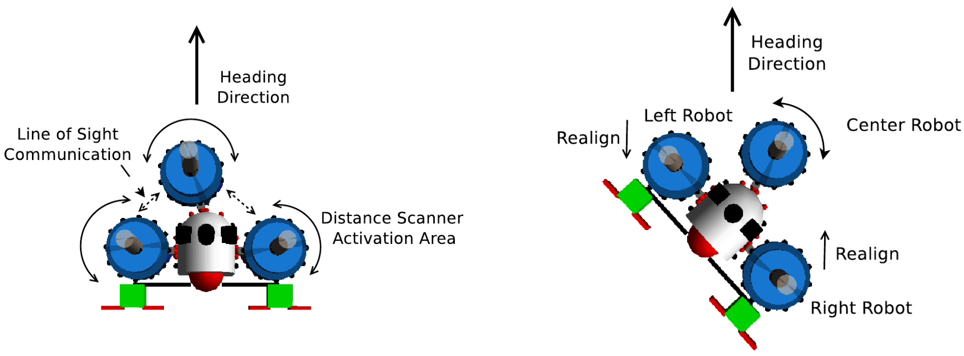
Notation	Meaning	Behavior
θ_P	Preferred direction when in $S_{stubborn}$ state	Social mediation
θ_S	Socially mediated angle $\theta_S \leftarrow \angle\sum_{i=0}^{k} e^{j\theta_i}$	Social mediation, collective transport
θ_0	Direction sent by social mediation behavior: θ_S in S_{social} state or θ_P in $S_{stubborn}$ state	Social mediation
$\theta_1 \dots \theta_k$	Direction received from the k neighbors	Social mediation
θ_G	Direction at which the goal is perceived	Collective transport
θ_O	Direction at which the obstacle is perceived	Collective transport
θ_{OA}	Direction at which the obstacle should be avoided. It has to take into account also θ_G if the goal is perceived.	Collective transport
θ_F	Direction of the shared environmental clue. All other directions are always relative to this	Collective transport
$\overline{\theta}_S$	Weighted time average of θ_S	Collective transport

Table 1: Explanation of the notation and behavior that uses it

perceive both goal direction and an obstacle and the others just the goal direction. Furthermore, in the case two or more robots perceive an obstacle, they can perceive it from different angles. Thus, one main issue in developing the controller is to make sure that the group can negotiate a direction to be followed, resulting from all this conflicting information. This part of the controller, called *social mediation*, is explained in Section 3.1. As a second step, the direction obtained by the social mediation behavior is used to properly produce the correct actuator's output to perform collective transport while continuously facing obstacles, as explained in Section 2. This is managed by the *collective transport* behavior, explained more in details in Section 3.2.

In the following, we will use a certain notation to denote directional information used in the behaviors. Table 1 explains and summarizes the notation.

Overall, the controller has been decomposed in multiple sub-behaviors (Figure 2). Logically, the controller can be decomposed in four main behaviors. The lower level behaviors are the *go to target*, *obstacle avoidance* and *social mediation*. The go to target behavior is used to query sensors and to obtain a goal direction, denoted as θ_G; the obstacle avoidance behavior is used to detect the presence of obstacles and the angle θ_O of the closest one. The social mediation behavior, explained in more details in Section 3.1, is used to obtain a heading direction, mediated through all the robots, to perform collective transport while assembled. We call this direction *socially mediated direction* and we denote it as θ_S. This heading direction has to take into account, at a given time, the presence or absence of obstacles, the angle at which obstacles should be avoided and the goal direction. Once this socially mediated heading direction is obtained, it is used by the high level behavior, the *collective transport* behavior, to perform collective transport by setting the correct actuators' output. The collective transport behavior is explained in more details in Section 3.2.



(a) (b)

Fig. 3: The carried robot and the carrying robots. (a) Distance scanner rotating activation ranges and line of sight communication. (b) Robot roles and actions that must be taken when misalignment is detected.

3.1 Multiple goal negotiation through social mediation

The social mediation behavior is the responsible for the negotiation of the direction of motion. The behavior uses two directional information, θ_S and θ_P: θ_S represents a socially mediated heading direction and θ_P the robot desired heading direction. The main idea behind the algorithm is the following. When an individual in the group has no information (i.e., they do not have information on goal or obstacle directions), it has an internal *state* set to S_{social}. In this state, the robot acts has a repeater, that is it computes θ_S, the average of the direction information available to its neighbors, and it sends this value around. However, when information (such as the obstacle direction) is available to the individual, its internal *state* is set to $S_{stubborn}$. In this state, it will rely its own preferred direction θ_P (for example the direction with respect to which to avoid the obstacle) instead of θ_S. Since all other robots are still sending θ_S, the opinion of the stubborn individual will soon diffuse in the entire group, that is θ_S through the group will converge to θ_P. The internal state of this behavior can be changed only by the top collective transport behavior, as explained in Section 3.2. Algorithm 1 depicts the steps executed at every control-step.

Algorithm 1 Social mediation control loop

1: $Receive(\theta_1, \theta_2, \ldots, \theta_k)$
2: $\theta_S \leftarrow \angle \sum_{i=0}^{k} e^{j\theta_i}$
3: **if** $state = S_{social}$ **then**
4: $\quad \theta_0 = \theta_S$
5: **else**
6: $\quad \theta_0 = \theta_P$
7: **end if**
8: $Send(\theta_0)$

At the beginning of the control loop, the robot receives the heading direction information $\theta_1, \theta_2, \ldots, \theta_k$ of its neighbors, where k represents the number of neighbors. Communication is restricted to all neighboring robots in range of sight, as we are using the range and bearing communication mechanism [10]. Due to the line of sight communication restriction, the robot attached at the center has $k = 2$ neighbors, whereas the other two have only $k = 1$ neighbor (see Figure 3a). The socially mediated heading θ_S is computed by averaging the directional information received by the neighbors (line 2), together to the robot own information θ_0.

Algorithm 2 Collective transport control loop

1: $[\theta_G, targetPerceived] \leftarrow PerceiveTarget()$
2: $[\theta_O, d, obstaclePerceived] \leftarrow PerceiveObstacle()$
3: $targetMisaligned = false$
4: **if** $targetPerceived$ **then**
5: $\quad targetMisaligned = IsTargetMisaligned(\theta_G)$
6: **end if**
7: **if** $targetMisaligned$ **or** $obstaclePerceived$ **then**
8: $\quad SocialMediation :: state \leftarrow S_{stubborn}$
9: **else**
10: $\quad SocialMediation :: state \leftarrow S_{social}$
11: **end if**
12: **if** $targetMisaligned$ **then**
13: $\quad SocialMediation :: \theta_P \leftarrow \theta_G$
14: **end if**
15: **if** $obstaclePerceived$ **then**
16: $\quad$ **if** $targetPerceived$ **then**
17: $\qquad w \leftarrow -\frac{d}{d_{max}} + 1$
18: $\qquad \theta_{AO} \leftarrow \angle w \cdot e^{j\theta_O + \pi} + (1 - w) \cdot e^{j\theta_T}$
19: $\quad$ **else**
20: $\qquad \theta_{AO} \leftarrow \angle e^{j\theta_O + \pi}$
21: $\quad$ **end if**
22: $\quad SocialMediation :: \theta_P \leftarrow \theta_{AO}$
23: **end if**
24: $SocialMediation :: ControlStep()$
25: $\overline{\theta}_S \leftarrow \angle(1 - \alpha) \cdot e^{j\overline{\theta}_S} + \alpha \cdot e^{j\theta_S}$
26: $ProportionalControl(\overline{\theta}_S)$

By using the mechanism depicted above, we are solving the issue on how to diffuse a heading direction information, perceived only by one individual, through the entire group, without the need of special signaling. This allows all robots in a group to be aware of the avoidance direction of an obstacle, even if only one member of the group can perceive the obstacle.

In the following section, we describe how this mechanism is used to achieve effective collective transport with obstacle avoidance.

3.2 Collective transport and obstacle avoidance

In this section we present the behavior responsible for collective transport with obstacle avoidance. This behavior uses the directional information computed in the social mediation behavior. In this behavior, θ_O denotes the direction at which the robot perceives an obstacle (if present), θ_G denotes the the goal direction (if perceived) and θ_{AO} denotes the avoidance direction of an obstacle (see table 1 for a summary). These directional information are always considered as relative to the direction of the shared environmental clue, denoted with θ_F.

At the beginning, sensors are queried to detect whether the target and/or obstacles are perceived (lines 1-2). The corresponding directions θ_G, corresponding to the goal, and θ_O, corresponding to the angle of the closest obstacle d, are also queried.

According to the information available to the robot (see Section 2) the internal state of the social mediation behavior is set (lines 7-11). If the robot perceives an obstacle with its distance scanner its state is set to $S_{stubborn}$. The same happens when the robot perceives that the current configuration is misaligned with respect to that target direction (see Figure 3b) thanks to the function *IsTargetMisaligned*() (line 5). This check needs θ_G and thus is done only if the target is perceived. In all other cases, that is when no obstacles are perceived and the compound is not misaligned, the state is set to S_{social} (line 10).

If a misalignment is perceived the robot tries to convince the others to realign by setting its desired direction θ_P to the goal direction θ_G (line 13).

In case an obstacle is perceived two things can happen. If no goal direction θ_G is available, the robots simply tries to avoid the obstacle at the the opposite angle at which the obstacle is perceived: $\theta_{AO} = \theta_O + \pi$. This angle θ_{AO} is set as desired direction θ_P (line 22). If, however, both the obstacle and the goal are perceived, the robot needs to compute the desired direction according to this two pieces of information: θ_{AO} and θ_G are thus averaged using a weighted average and the result is set as desired direction θ_P (lines 16-18). The weighted average uses a weight $w \in [0, 1]$ dependent on the distance between the robot and the obstacle (line 17) which represents how urgent it is to avoid obstacles: it is 1 when the obstacle is very close ($d = 0$) and 0 when it is far away ($d = d_{max}$, the maximal perception range of the obstacle avoidance behavior). We set $d_{max} = 0.75$ meters, half of the maximal range of the distance scanner.

In the case that both a misalignment and an obstacle are perceived the priority is given to obstacle avoidance and the misalignment is ignored.

Once θ_P is computed, the control step of the social mediation behavior is executed (line 26). As a result, the angle θ_S is computed by the social mediation behavior. This angle is then filtered by computing a time average (line 27) to filter out the effect of noise. Finally, a proportional control is performed using, as a reference, the filtered direction $\overline{\theta}_S$ which is interpreted as a difference with respect to the common environmental clue direction θ_F. This simple proportional control tries to follow the direction $\overline{\theta}_S$ by considering the robot attached to the left as the left wheel of the compound system and the robot attached to the right as a right wheel. The robot at the center independently controls the two wheels speed still depending on the proportional control rule.

To summarize the idea, the collective transport behavior interacts with the social mediation behavior to obtain a socially mediated direction $\overline{\theta}_S$ which is consistent in the group and allows a coherent motion. The social mediation behavior needs to be set in the appropriate state ($S_{stubborn}$ or S_{social}), according to which information is available to the robot. It also needs the direction θ_P to be sent to the neighbors in case it is in $S_{stubborn}$ state. θ_P can be the direction to the goal, the direction to avoid an obstacle or direction which takes into account both the goal and obstacles. The behavior achieves coherent collective motion since the socially mediated direction, that is the direction negotiated through the entire group, is used together with a proportional control rule.

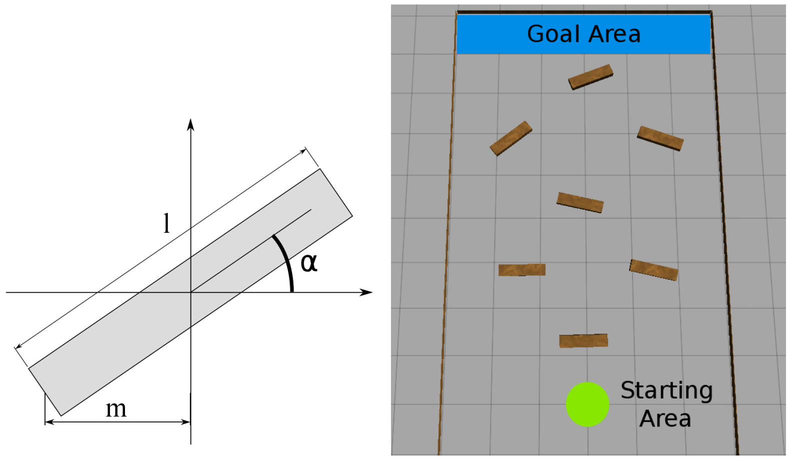
4 Experiments and results

We performed three sets of experiments. The first two sets consider a simple environment, where we generate an obstacle at the center of the arena with varying angle α (see Figure 4a). For each setting, we executed 100 runs. Our hypothesis is that the more α tends to 0, the longer it takes to avoid the obstacle in collective transport. We also expect that the developed behavior is robust enough to always accomplish the task (move from an initial to a goal location, see Figure 4b) in this simplified setting. We hence report the completion times as a function of varying α. The difference between the first and the second set of experiments is that in the first we just analyze the impact of the angle α by keeping the projected size of the obstacle m fixed (Figure 4a), whereas in the second set we also analyze the impact of the varying projected size, keeping l fixed. Execution times are reported in time-steps. Each simulated second corresponds to 10 control-step.

In the third and last set of experiments, we generate at random some more complex environments, of the type depicted in Figure 4b. The goal here is to report the success rate of the behavior and understand, in case of failures, how to improve it. We executed a total of 1000 runs, where in each run the angle and a small offset of the position of each obstacle is generated at random.

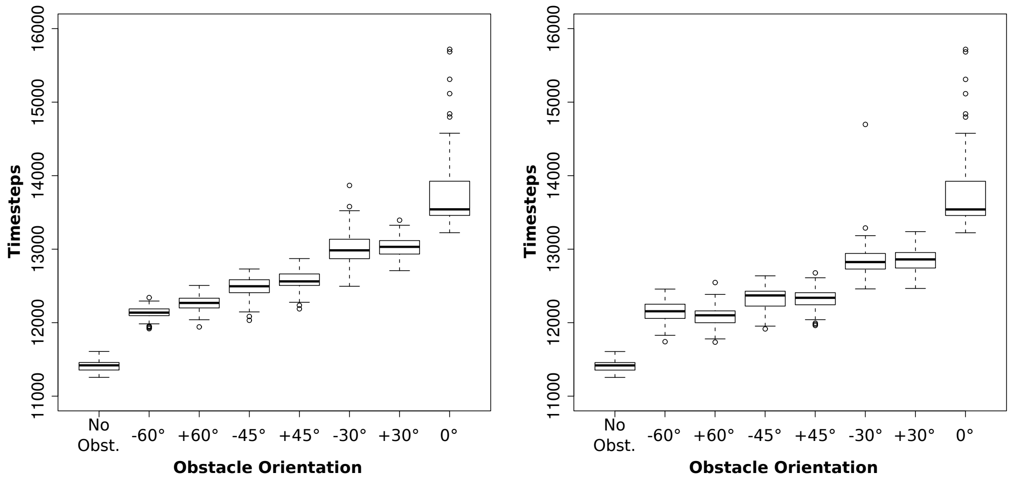
Figure 5 shows the results for the first two sets of experiments performed in the simple environments. As we can see, the initial hypothesis can be accepted, as the execution times solely depends on α and not on the projected length m of the obstacle. In fact, execution times increase with the increasing values for α. The closer the obstacle angle is to the angle perpendicular to the direction of motion, the longer it takes to be avoided.

The case $\alpha = 0$ is particularly problematic. Average times are much higher, and many more outliers are present (not fully shown due to scale differences). This is explained by the fact that,



(a) (b)

Fig. 4: (a) The controlled obstacle's parameter in the first two sets of experiments and (b) an example of complex environment. S denotes the starting area, G the goal area



(a) (b)

Fig. 5: Box plot of completion time for the experiment set with fixed w (a) and for fixed l (b)

when an obstacle faces perpendicularly the direction of motion, the avoidance direction θ_{OA} takes some time to converge to one of the two possible sides where the obstacle can be avoided. All the runs were successful and no collision was registered.

In the third set of experiments, results showed a remarkable success rate of 96%. In the remaining 4% of the cases, robots hit an obstacle and hence the corresponding run was terminated. After analyzing failures cases separately, we found out that they were all due to a too slow misalignment correction performed by the robots when not facing correctly the goal direction after avoiding an obstacle. The alignment was not corrected in time before the next obstacle, and hence robots were hitting it with the blind side of the carried structure, corresponding to the region of the object where the robots cannot attach. These failures suggest that a more robust misalignment correction behavior might be needed before porting the presented methodology to the real robots. A video showing one typical run for this set of experiments can be found in [12].

5 Conclusion and future work

In this paper, we presented a novel method to tackle a task that has received limited attention in the literature: obstacle avoidance in collective transport. The task involves collective transport of an irregular object by a group of three robots. In this task, robots can only assemble in a semicircle around the robot and they have to avoid obstacles while navigating to a given goal location.

The proposed method consists of two interacting behaviors. The first behavior is called social mediation and is used to perform negotiation of an heading direction which takes into account possibly conflicting perceptions of the members of the group. The second behavior achieves collective transport, using this mediated heading direction, while at the same time maintaining an alignment of the carried structure which maximizes the perception range of obstacles.

Experiments were performed in a simple arena with one obstacle placed at different angles and in a more complex arena with several obstacles. Results in the simple arena show that the efficiency (inversely linked to execution times) of the behavior solely depends on the angle at which obstacles are placed, and that the more the obstacle is placed perpendicularly to the direction of motion the more time it takes to avoid it. In a more complex environment, we tested the robustness (success rate) of the proposed approach, obtaining 96% of success.

This work can be extended in a number of directions. As a first step, the proposed methodology can be validated on real robots. We speculate that the social mediation method, being a very high level behavior, will need few adaptations for the real robots experiments, whereas the collective transport might need some adjustments, especially from the point of view of ensuring a correct vehicular dynamics which minimizes wheels slipping. Second, some of the assumptions made in this work could be relaxed. For example, it can be interesting to investigate how to solve the task by assuming that robots do not know the position of the irregular object at which they are assembling or with which angle. Third and more ambitiously, a long term goal would be to understand how to control a group of an arbitrary number of robots, connected between each other and/or to an irregular object at different positions. In this case, we speculate that the social mediation methodology can be extended to tackle dynamic negotiation of heading direction with an arbitrary number of robots.

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