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Study on the Cooperative Transportation of a Load Using Swarm Robots

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Abstract — *This paper proposes a formation control scheme for transporting a plate using mobile robots through an unknown environment while only making use of friction and normal forces between the plate and the robots. The scheme includes the calculation of the normal forces by solving a linear complementarity problem, and the formation control of the swarm of robots while they keep the plate stable. To this end, possible stability conditions of the transportation mechanism are investigated and used to formulate an optimization problem describing the control task. The approach makes use of a repeated Voronoi decomposition. The robots are controlled distributedly using augmented Lagrangian particle swarm optimization to solve the formulated optimization problem which makes it possible to enforce constraints on the movements of the robots to allow for a successful transportation of the plate. The proposed scheme is extensively tested in various simulations and the results show that the transportation mechanism works successfully.*

1 Introduction

In recent years, autonomous agents, including mobile robots, have increasingly come into the focus of academic and industrial users, e.g., investigating formation control of mobile robots that maneuver through an unknown environment while avoiding obstacles [1, 2]. When simple individual robots gather together, their application is enlarged, e.g., for the cooperative search of an unknown environment by a swarm [3] or for transporting a load [4].

Cooperative transportation of a load is an interesting application of swarm robotics in the sense that a swarm creates a formation around an object and tries to transport it to the desired position. This usually is done by prehensile or non-prehensile approaches. In prehensile approaches, the robots and the load are rigidly connected and object manipulation and motion control of mobile robots are investigated [4, 5]. In [4], the mobile robots are physically connected to an object by their grippers and transport it by a leader-follower system. In non-prehensile approaches, the load is carried by pushing or rolling without a rigid connection to the object [6, 7].

Instead of the mentioned methods, we propose a new approach where a formation of omnidirectional mobile robots transports an elastic plate purely by friction and normal forces between the plate and the robots [8, 9, 10]. The elastic plate is carried by pins that are attached to the top of the robots. Instead of closure forces to grasp the plate or pushing forces, the absence of a rigid connection gives the robots the ability to move and stick or slip under the plate. Therefore, they can change the respective force direction and position while they keep the stability of the plate. However, if more than three robots are under the plate, the system is overdetermined. In addition, the displacement constraints at the contact points are unilateral and thus, to calculate the normal forces, a linear complementarity approach is used.

The formation control problem is another aspect of this research that shall be taken into account. To deal with this issue, various approaches can be considered such as leader-follower approaches [11, 12], artificial potential fields [13], behavioural and virtual structures [14, 15], graph theory [2, 16] and consensus-based approaches [17]. So far, we have investigated three approaches for controlling the formation and path planning to transport an elastic plate by this mechanism. In [8], an improved artificial potential field method (APF) is utilized for path planning and formation control of the mobile robots by constructing a potential field with local maxima at the positions of obstacles and a global minimum at the goal position. Therefore, the robots are effectively subjected to a virtual force field with an attractive force generated by the goal and repulsive forces generated by the obstacles. Although APF is a simple approach to be implemented on hardware, it has inherent, difficult to solve, drawbacks, e.g. local minima that the robots may get stuck in. Therefore, APF cannot be utilized for many difficult environments like maze-like environments.

Other approaches are based on distributed model predictive control [9, 10]. The scheme includes a graph-based path planning strategy that does not rely on discretization of the environment, with the obstacles having any desired polygonal shape. The strategy permits the robots to construct a map of the environment during the motion and thus, they can successfully navigate through maze-like environments using a memory functionality. A distributed model predictive controller finds the control inputs for the swarm while satisfying constraints to limit the slipping between the load and the robots. Hence, at first a sequential distributed model predictive control (SDMPC) for transporting the plate was proposed in [9]. Then, the simulation and experimental results of SDMPC were compared with an approach based on iterative distributed model predictive control (IDMPC) [10].

These three approaches aim to keep the formation's center and the center of the plate as closely together as possible. Therefore, the formation shape and the movements of the robots are limited to specific shapes. Also, the stability of the plate is not explicitly considered in the control schemes. However, by using this type of manipulation mechanism, relative movements of the robots and highly dynamic driving maneuvers will sometimes lead to a sliding plate, resulting in a displacement between the formation center and the center of the plate. In the worst case, this may lead to an instability of the system, where the plate falls off the robots.

Considering this, the novel contribution investigates the stability of the plate. To this end, the possible stability conditions of the transportation mechanism are analyzed. Based on this, a new formation of the mobile robots using a Voronoi decomposition is calculated. Hence, there is no need to predefine the formation shape, and it can be applied to many scenarios. Also, to enforce constraints on the movements of the mobile robots, each robot is controlled using a distributed controller based on augmented Lagrangian particle swarm optimization (ALPSO) [18], with the aim to guarantee the stability of the transportation mechanism.

The presented paper is organized as follows. Section 2 discusses the system modelling and the formulation of the plate transportation mechanism. This includes the models of the robots and the elastic plate, as well as the friction and normal forces. Thereafter, Section 3 deals with a brief summery of the utilized path planning scheme. The details of the implemental formation control method and the proposed control algorithm are explained in Section 4. Finally, various demanding scenarios are carefully simulated using the proposed scheme in Section 5 and the results are discussed.

2 System Modelling

The setup is shown in Figure 1, with the right-hand side showing. The figure shows that four robots are moving in the x-y-plane and the plate is carried above the robots and is in contact with the small pins attached to the top of the robots. In this research, the Robotino, which is manufactured by Festo [19], is used. It is a holonomic omnidirectional robot, therefore all its constraints are integrable and it can move freely in any direction of the plane. The modelling follows [8, 9] with the information essential for the needs of this paper summited subsequently. Considering the friction caused by the mechanical parts of the drive train, a Robotino is modelled as a point mass

$$\boldsymbol{M}\ddot{\boldsymbol{q}}_i + \boldsymbol{D}\dot{\boldsymbol{q}}_i = \boldsymbol{u}_i, \tag{1}$$

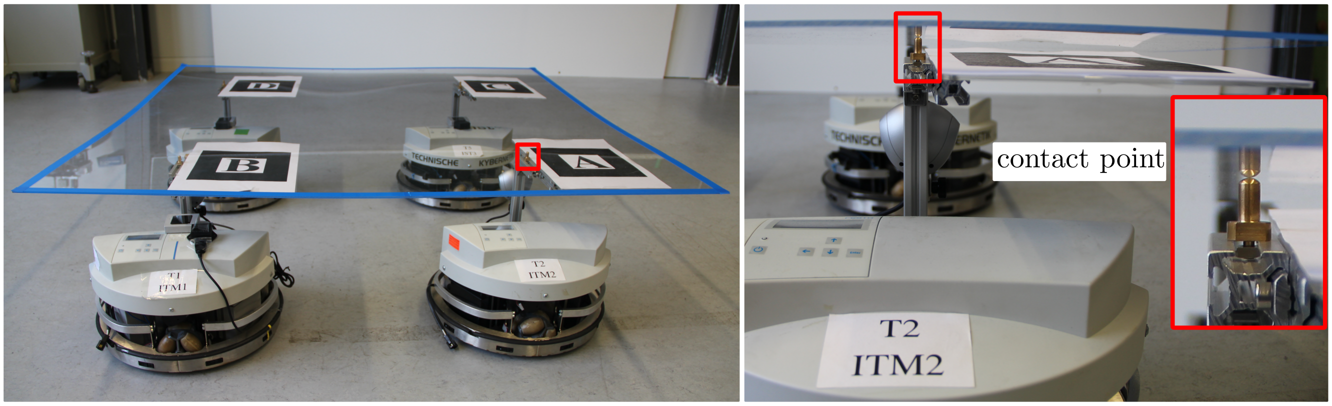


Fig. 1: Experimental setup.

where $\boldsymbol{q}_i \in \mathbb{R}^2$ is the position of a mobile robot in the inertial frame of reference and the diagonal matrices $\boldsymbol{M} \in \mathbb{R}^{2\times 2}$ and $\boldsymbol{D} \in \mathbb{R}^{2\times 2}$ are the mass and damping matrices, respectively. The model with the system states $\boldsymbol{x} = [\boldsymbol{q} \quad \dot{\boldsymbol{q}}]^T$ is represented in the state space form as

$$\dot{\boldsymbol{x}}_i = \begin{bmatrix} \boldsymbol{0} & \boldsymbol{E} \\ \boldsymbol{0} & -\boldsymbol{M}^{-1}\boldsymbol{D} \end{bmatrix} \boldsymbol{x}_i + \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{M}^{-1} \end{bmatrix} \boldsymbol{u}_i := \boldsymbol{A}\boldsymbol{x}_i + \boldsymbol{B}\boldsymbol{u}_i. \tag{2}$$

Here, $\boldsymbol{E}$ is the identity matrix and the propulsion forces in the two coordinate directions form the control input $\boldsymbol{u}_i \in \mathbb{R}^2$. The plate is assumed to be a cuboid of uniformly distributed mass with six degrees of freedom. The plate's equation of motion has the form

$$\boldsymbol{M}_{\mathrm{p}}(\boldsymbol{y})\ddot{\boldsymbol{y}} + \boldsymbol{k}_{\mathrm{p}}(\boldsymbol{y}, \dot{\boldsymbol{y}}) = \boldsymbol{q}_{\mathrm{p}}(\boldsymbol{y}) \tag{3}$$

where the applied forces, the force of gravity in the negative z-direction, the normal and friction forces at the contact points, and their generated moments are considered in $\boldsymbol{q}_{\mathrm{p}}$.

The contact area between each pin and the plate is modelled as a point contact with Coulomb friction. The friction force $\boldsymbol{F}_{\mathrm{F}} \in \mathbb{R}^3$ is modelled in the form

$$\boldsymbol{F}_{\mathrm{F}}(\boldsymbol{v}_{\mathrm{slip}}) = F_{\mathrm{N}}\, \gamma_1 \tanh(\gamma_2\ |\boldsymbol{v}_{\mathrm{slip}}|)\, {}^{\boldsymbol{v}_{\mathrm{slip}}}/_{|\boldsymbol{v}_{\mathrm{slip}}|} \tag{4}$$

with $\boldsymbol{F}_{\mathrm{F}}(\boldsymbol{0}) := \boldsymbol{0}$, see [20]. The normal force acting on the plate is represented by F_{N} and $\boldsymbol{v}_{\mathrm{slip}} \in \mathbb{R}^3$ is the slip velocity between the respective pin and the contact point on the plate. While γ_1 is a material-dependent parameter, γ_2 is a design parameter modifying the function's sigmoid shape.

Since the displacement constraints at the contact points are unilateral, the calculation of the normal forces is non-trivial. Hence, the normal force at the contact point shall be calculated to obtain the overall model of the system. When more than three robots are under the plate in a general configuration, the problem is overdetermined. To find the solution, the plate is discretized using the finite element method with linear, quadrilateral Reissner-Mindlin plate elements with four nodes. The common approach of the direct stiffness method simply sets the displacements of the contact nodes to be zero. This leads to incorrect results, since unphysical pulling normal forces in the negative z-direction can occur. This is demonstrated in a simulation result in Figure 2(a).

To ensure that only positive normal forces occur in the z-direction on the plate, the equations are reformulated as a linear complementarity problem (LCP). When a robot looses the contact to the plate, the respective normal force would be zero. The detailed formulation of an appropriate LCP problem to find the normal forces can be found in [8]. The simulation of an elastic plate supported by six mobile robots is shown in Figure 2. The blue-colored circle signifies a negative value of the corresponding normal force, belonging to an incorrect solution obtained with the direct stiffness method. The yellow-colored circle indicates that the respective mobile robot has no contact with the plate, while the red-colored circles represent the normal forces in the positive z-direction. Figure 2(b) obtained by solving LCP shows the plate lifts-off correctly.

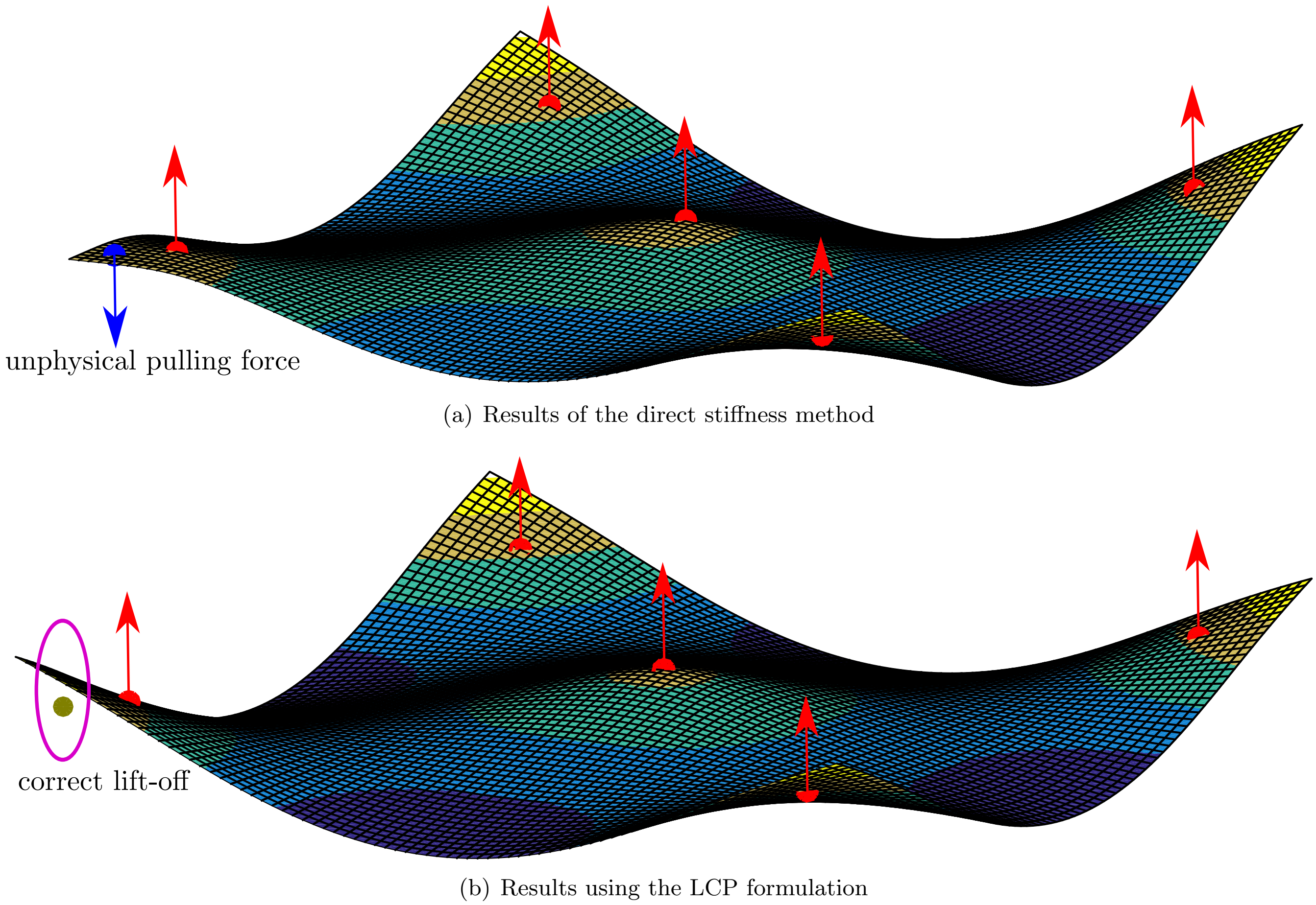


Fig. 2: Calculation of the normal forces by LCP and the direct stiffness method, from [8].

3 Path Planning

In this study, the path planning scheme from [9] is used, with a broad overview of the scheme given below. Each robot has a sensor delivering distance readings within a limited distance to detect the positions and shapes of surrounding obstacles. The robots sense their environment in each time step and a map is generated using the sensor information. The generated map is used to plan a path from the current position to the goal. This path can be planned for the formation's center of mass or a specific mobile robot. The respective path is not parametrized in time and thus, it is undefined at what time the formation shall reach which point of the path.

In order to calculate the reference path of the formation's leader, a graph is defined that includes the shapes of obstacles. To this end, it is considered that the obstacles consist of convex polytopes. Non-convex obstacles can be represented by multiple convex obstacles. The obstacles in the constructed map are represented as the intersection of half-planes, i.e. by a finite set of linear inequalities.

As the first step in the path planning, a buffer zone around the obstacles shall be taken into account. The buffer zone is the minimum distance that a mobile robot must keep away from the obstacles. Using this, one can be sure about the feasibility of a path toward the goal. Enlarged versions of the obstacles are calculated that contain the buffer zones. Algorithmically, they are saved both in their vertex and their half-plane representations. All obstacles vertices are collected in the set V_{ob}. If vertices of newly discovered obstacles are contained in the buffer zone of any other obstacle, they will be removed from V_{ob} and only necessary vertices remain.

Then, a graph with the set of nodes $V := V_{\mathrm{ob}} \cup \{\boldsymbol{g}, \boldsymbol{s}\}$ is constructed that contains potential paths from the current position $\boldsymbol{s}$ node to the goal position $\boldsymbol{g}$ node. The weighted, undirected graph (V, E, w), $E \subseteq V \times V$, contains a suitable set of edges E and corresponding edge weights $w\colon E \to \mathbb{R}$, i.e. the Euclidean distance between corresponding nodes. All those edges are added to the graph for which the straight line between the two corresponding nodes does not lead through one of the enlarged obstacles.

The constructed graph contains possibly many feasible paths toward the goal. Hence, Dijkstra's algorithm [21] is utilized to find the shortest path from the current start position node to the goal node. The optimal path is represented by a sequence of nodes $V_{\text{opt}} = \begin{bmatrix} v_1 & v_2 & \cdots & v_{\text{g}} \end{bmatrix}$ where the start node is shown by v_1 and v_{g} is the goal node.

Using spline interpolations in the x- and y-dimensions of the points in V_{ob}, a continuously parametrized path based on the calculated graph-theoretic path is calculated. More details about the utilized path planning approach and the memorizing functionality can be found in [9]. Based on this path planning approach, the following section deals with the formation control strategy.

4 Formation Control Using ALPSO

The fundamental challenge of this paper is that n omnidirectional mobile robots shall transport a thin elastic plate from a given start position $\boldsymbol{s} \in \mathbb{R}^2$ to a given goal position $\boldsymbol{g} \in \mathbb{R}^2$ while they keep the plate stable. To this end, the center of mass of the plate shall always be in the convex hull created by the swarm robots under the plate, otherwise the plate will fall off the robots. Therefore, the formation shape plays a vital role. In the field of formation control, it is common that a certain formation is defined, e.g. four robots shall stay in a square formation. In these cases, the chosen formation shape could be defined before system runtime by defining the desired robot positions relative to the formation's center. In order to have more freedom to do complicated maneuvers, it is more favorable if arbitrary and dynamically changing desired formation shapes can be computed in each time step. For instance, this gives the ability for shrinking a formation so that it can pass through narrow passages. By dynamically changing the formation, each robot knows its desired position relative to a coordinate system located in the plate' center and each robot runs its own distributed controller.

In order to create a convex hull around the plate's center, the robots shall spread out under the plate. Hence, a deployment problem is solved in each time step to find the desired formation shape. The robots shall deploy themselves in a convex polygon, i.e. below the plate's area, such that they have good coverage. To find the desired formation, at first space partitioning shall be solved. Hence, we are solving the coverage problem to decompose the space. To this end, suppose that n mobile robots are at the points $(\boldsymbol{p}_1, ..., \boldsymbol{p}_n)$. The aim is to find the best partitions $\{\mathcal{W}_1, ..., \mathcal{W}_n\}$ of the polygon $\mathcal{W}$ which maximize the coverage. Therefore, the total cost function is

$$\mathcal{H}(\boldsymbol{p}_1, ..., \boldsymbol{p}_n, \mathcal{W}) = \sum_{i=1}^{n} \int_{\mathcal{W}_i} \|\boldsymbol{q} - \boldsymbol{p}_i\|^2 \mathrm{d}\boldsymbol{q}. \tag{5}$$

The Voronoi partition $\mathcal{W} = \mathcal{V}(\boldsymbol{p}_1, ..., \boldsymbol{p}_n) = \{\mathcal{V}_1, ..., \mathcal{V}_n\}$ is the unique partition that minimizes the cost function $\mathcal{H}(\boldsymbol{p}_1, ..., \boldsymbol{p}_n, \mathcal{W})$ for the given set point where

$$\mathcal{V}_i = \{\boldsymbol{q} \in \mathcal{W} \mid \|\boldsymbol{q} - \boldsymbol{p}_i\|^2 \leq \|\boldsymbol{q} - \boldsymbol{p}_j\|^2 \quad \forall j \neq i\}. \tag{6}$$

The desired position of each mobile robot is the centroid of its own Voronoi cell

$$\boldsymbol{c}_{\mathcal{V}_i} = \frac{1}{A_{\mathcal{V}_i}} \int_{\mathcal{V}_i} \boldsymbol{q} \mathrm{d}\boldsymbol{q}. \tag{7}$$

In each time step, the Voronoi partition is recalculated using the positions of the mobile robots as generators. Then, they move toward the centroid of their own Voronoi cell. Finally, the mobile robots converge to one of the critical points of $\mathcal{H}(\boldsymbol{p}_1, ..., \boldsymbol{p}_n, \mathcal{W})$. As an extension, it is possible to employ weighted

Voronoi decomposition to define areas of particular interest under the plate. In order to make sure the plate always remains in the convex hull created by the formation, a buffer zone of width ε_f is subtracted from this convex hull and a constraint will be considered.

The planned path is utilized for the, possibly virtual, leader of the formation. Subsequently, the formation's center of mass is considered as the virtual leader of the swarm, navigating all robots to the target position. When the distance between a mobile robot and an obstacle is less than a predefined threshold, the real robot, that is in the danger area, takes the lead. As will be seen in the simulation results, this gives the swarm the ability to do complicated maneuvers, e.g. transporting a plate through a narrow passage that just only one mobile robot can pass at a time.

Another aspect of the researched problem is that a mobile robot shall avoid collisions with the other mobile robots and the obstacles. To deal with this issue, a safety buffer zone is defined around each mobile robot, so that other robots cannot enter this area. Also, the Euclidean distance between the detected obstacle point $\boldsymbol{r}_\mathrm{o}$ and the robot position is constrained to be larger than $d_\mathrm{r} + \varepsilon_\mathrm{o}$ where d_r is the radius of a Robotino and ε_o is the minimum distance to an obstacle.

If the formation's center $\boldsymbol{c}_\mathrm{r}$ coincides with the plate's center of mass $\boldsymbol{c}_\mathrm{p}$, transportation is easier since the mobile robots can do symmetric movement. This is the approach from [8, 9, 10] where the formation is shrunk symmetrically in a coordinated way to keep the center of masses of formation and plate very close together. However, this way restricts the formation to symmetric shapes and it might decrease the ability of the system to do more complicated maneuvers. On the other hand, due to uncertainty in the real experiments, it is not possible to keep these two points close for extended periods of time. Hence, a circle with radius d_rp around the formation's center of mass is considered in order to force the plate's center to stay there. This constraint also helps to keep the plate stable by keeping the plate's center of mass inside the stability area.

The schematic of the conditions for a group of four mobile robots is depicted in Figure 3. This figure shows that the area under the plate, i.e. the polygon $\mathcal{P}$, is partitioned into Voronoi cells depicted by brown lines. Also, the safety areas around the mobile robots and the obstacle are drawn by the buffer zones ε_r and ε_o, respectively. The plate's safety margin defines an area in which the mobile robots shall be located. It is a smaller version of the plate's polygon $\mathcal{P}$ by buffer zone ε_p. The plate's stability zone is illustrated by lines dashed in black where the plate's center shall always be there. This zone is a smaller version of the formation's convex polygon $\mathcal{F}$ by buffer zone ε_f. Also, the circle with the radius d_rp around the formation's center of mass is shown in red color.

On the basis of constraints, the problem is turned into an optimization problem. We are seeking an optimal solution for a distance-based potential function which satisfies our constraints. A suitable cost function for robot i at time step k can be defined as

$$J(\boldsymbol{x}_i^k, \boldsymbol{u}_i^k) = \|\boldsymbol{c}_{\mathcal{V}_i} - \begin{bmatrix}\boldsymbol{E} & \boldsymbol{0}\end{bmatrix}(\boldsymbol{A}_\mathrm{d}\boldsymbol{x}_i^k + \boldsymbol{B}_\mathrm{d}\boldsymbol{u}_i^k)\|^2 \tag{8}$$

to force the robots to move toward the center of Voronoi cells. Here, $\boldsymbol{A}_\mathrm{d}$ and $\boldsymbol{B}_\mathrm{d}$ are system and input matrices from the discrete-time system. Subsequently, the optimization problem to be solved by each of the robots can be given in the form

$$\begin{aligned}
\underset{\boldsymbol{u}_i^k}{\text{minimize}} \quad & J(\boldsymbol{x}_i^k, \boldsymbol{u}_i^k) \\
\text{subject to} \quad & \boldsymbol{v}_\mathrm{min} \le \begin{bmatrix}\boldsymbol{0} & \boldsymbol{E}\end{bmatrix}\boldsymbol{x}_i^{k+1} \le \boldsymbol{v}_\mathrm{max} \\
& \|\begin{bmatrix}\boldsymbol{E} & \boldsymbol{0}\end{bmatrix}\boldsymbol{x}_i^{k+1} - \boldsymbol{r}_\mathrm{o})\|^2 \ge d_\mathrm{r} + \varepsilon_\mathrm{o} \\
& \psi(\begin{bmatrix}\boldsymbol{E} & \boldsymbol{0}\end{bmatrix}\boldsymbol{x}_i^{k+1}, \mathcal{P}) \le -\varepsilon_\mathrm{p} \\
& \psi(\boldsymbol{c}_\mathrm{p}, \mathcal{F}) \le -\varepsilon_\mathrm{f} \\
& \|\boldsymbol{c}_\mathrm{p} - \boldsymbol{c}_\mathrm{r}\|^2 \le d_\mathrm{rp} \\
& \|\boldsymbol{x}_i^{k+1} - \boldsymbol{x}_j^k\|^2 \ge 2(d_\mathrm{r} + \varepsilon_\mathrm{r}), \quad \forall j \ne i
\end{aligned} \tag{9}$$

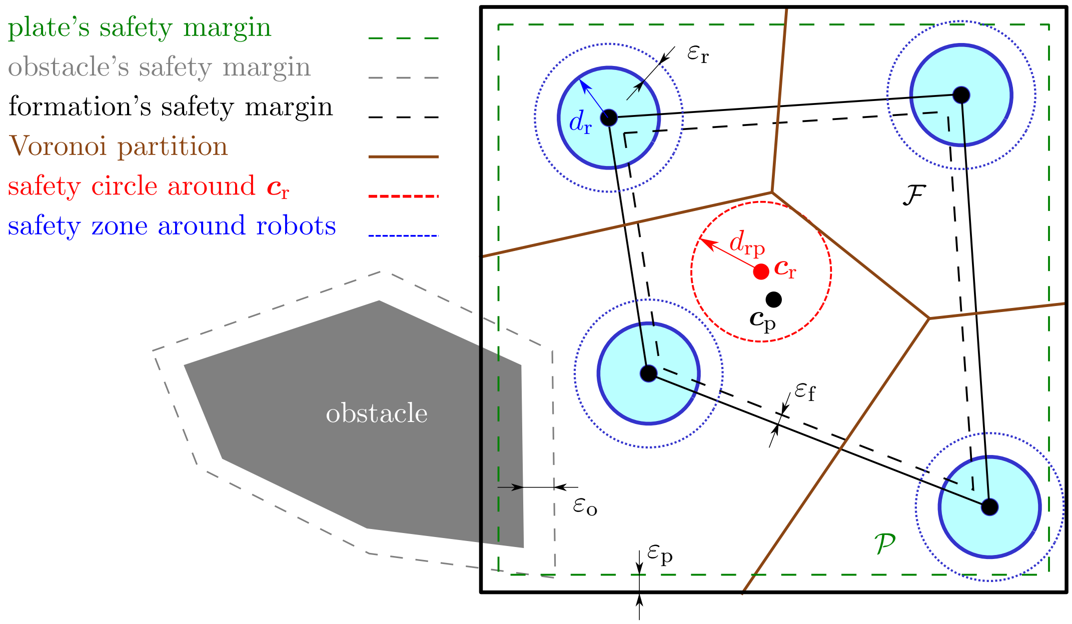


Fig. 3: Schematic of transporting a plate with conditions.

where $\psi(\boldsymbol{s}, \mathcal{W})$ is a function that calculates the distance between the point $\boldsymbol{s}$ and the polygon $\mathcal{W}$. If the point is located within the polygon, the results will be negative.

To solve the optimization problem, augmented Lagrangian particle swarm optimization (ALPSO) [18] is utilized. ALPSO is a powerful stochastic optimization approach for solving nonlinear, non-differentiable, or non-convex engineering problems where equality and inequality constraints are included. This approach is a combination of the structure of the basic PSO technique and an extended non-stationary penalty function approach.

5 Simulation Results

The simulations have been implemented in Matlab R2017b. For detecting the obstacles and mapping the environment, it is assumed that each mobile robot has a sensor that can sense distance measurements around its center of mass. The sensor is simulated by casting virtual light rays in all directions around the robots. The virtual light rays are sampled and the intersection of the rays with visible surfaces of each obstacle are calculated. Therefore, similar to real-world sensors, the distance measurements are of limited accuracy. More detail about sensor simulation and the memorization of obstacles can be found in [9].

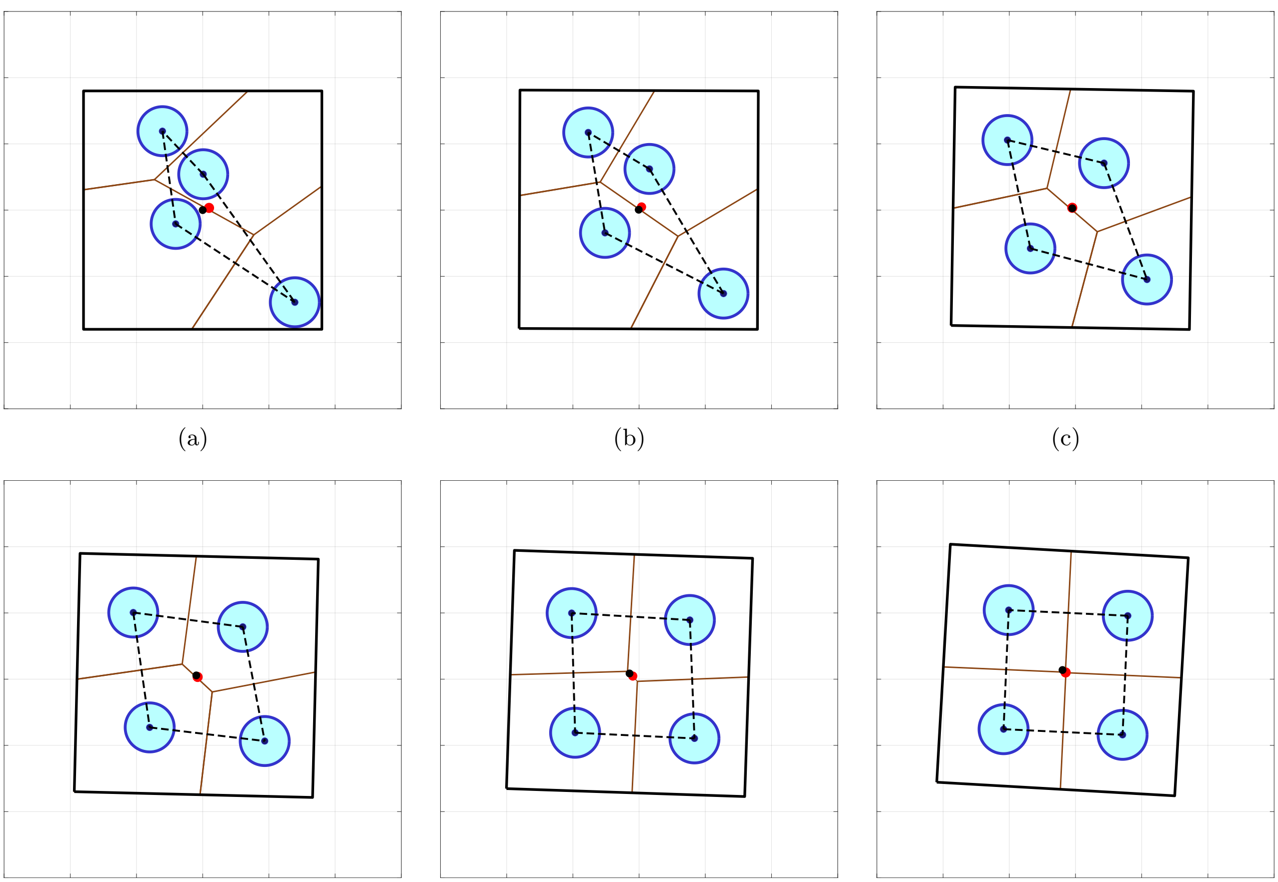
In the implementation, there might be multiple obstacles in the field of view at once. Therefore, a heuristic approach using the measured distance values is implemented in order to guess where one obstacle ends or begins. By implementing this strategy, the robots can memorize their surroundings to navigate through very intricate environments. To transport the plate through narrow passages, it is assumed that the plate moves above the obstacles so that the formation can shrink to squeeze through the passage. If the obstacles are taller than the plate's traveling height, to prevent collisions between the obstacles and the plate, one could increase ε_o to a value larger than the width of the plate.

Here, three scenarios are simulated to analyze the performance of the proposed scheme. In all of the following figures, the obstacles are drawn as dark gray areas. The robots are represented by light blue circles with dark blue outlines and the plate is drawn as a transparent rectangle with thick black outlines. The pins supporting the plate are located in the robot's rotation centers and it is drawn by dark blue circles. The convex polygon created by the robots is depicted by the lines dashed in black and the Voronoi diagram is depicted by brown lines. The plate's center and the formation's center of mass are shown by black and red circles, respectively.

The first scenario, a simple deployment simulation, is shown in Figure 4. In this simulation, four mobile robots are located in a dangerous way in Figure 4(a). Over time, the Voronoi diagram converges to a centroidal Voronoi tessellation. As can be gathered from the figure, the closeness of the plate's center and the formation's center is advantageous. The robots converge to the desired positions while they keep these two points close together. If there exists a big gap between these two points, the robots shall move faster to compensate the error using the slippage between the pin and the plate. However, due to the velocity constraint, this is not possible.

Figure 5 shows the second scenario, with five mobile robots transporting a plate through a narrow passage where only one mobile robot can pass at a time. In this simulation, the robots pass one by one through the passage while they avoid the obstacles and collisions with each other. This simulation clearly shows the performance of the scheme when the formation is changing constantly over time. The trajectory of the formation's center, which is marked by the line dashed in red, shows how the formation's center moves to pass through these obstacles. Also, switching of the leadership helps the robots to navigate the formation. Comparing the Figures 5(a) and 5(l) reveals that the last and the first formation shapes are different and this is caused by different local minima of the deployment problem.

Also, the velocity of the robot located in the lower left of the formation in Figure 5(a) is shown in Figure 6. This figure shows that the formulated optimization problem enforces the robots to not move faster than the maximum velocity of 0.8 $\frac{\mathrm{m}}{\mathrm{s}}$.



(a) (b) (c) (d) (e) (f)

Fig. 4: Deployment under the plate.

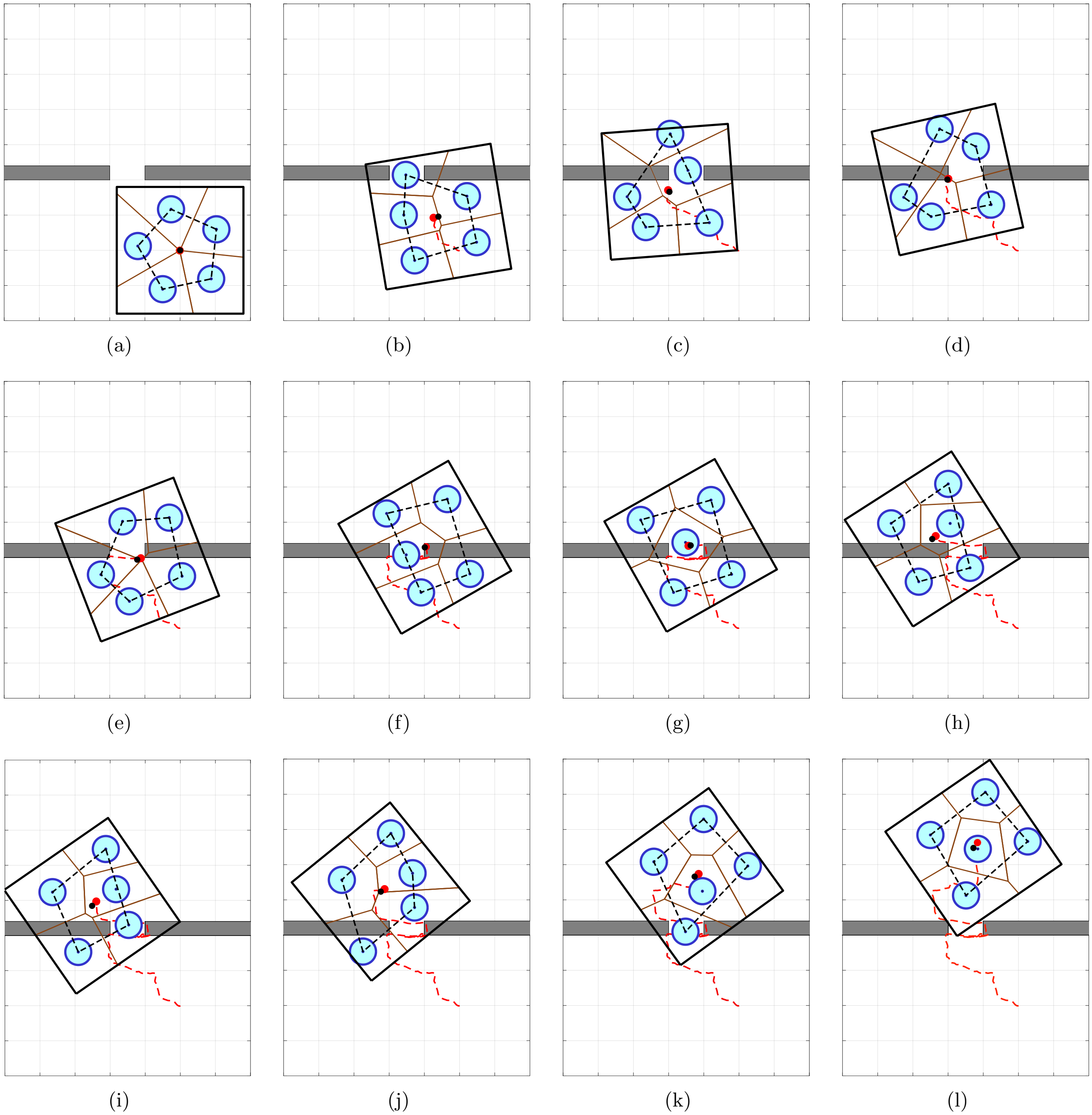


Fig. 5: Transporting an elastic plate through a narrow passage.

The third scenario is shown in Figure 7 where three mobile robots transport the plate in an unknown environment to the desired position. In the following simulation, the start position of the formations center of mass is drawn by an asterisk and the goal position is marked by a diamond. As it can be seen in Figures 7(b) to 7(d), the swarm starts to move toward the goal. When it finds that there is no direct way, the path is changed to another direction. This is done by memorizing the environment as described in [9]. The results show that the formation is successfully navigated through even very intricate environments by using the memorizing functionality.

The next challenge is a narrow tunnel that is very hard for two robots to pass simultaneously. Figures 7(e) to 7(h) show how the robots transport the plate through this tunnel. Then, the robots reach a narrow passage that is different from the passage in Figure 5. Here, the obstacles restrict the movement

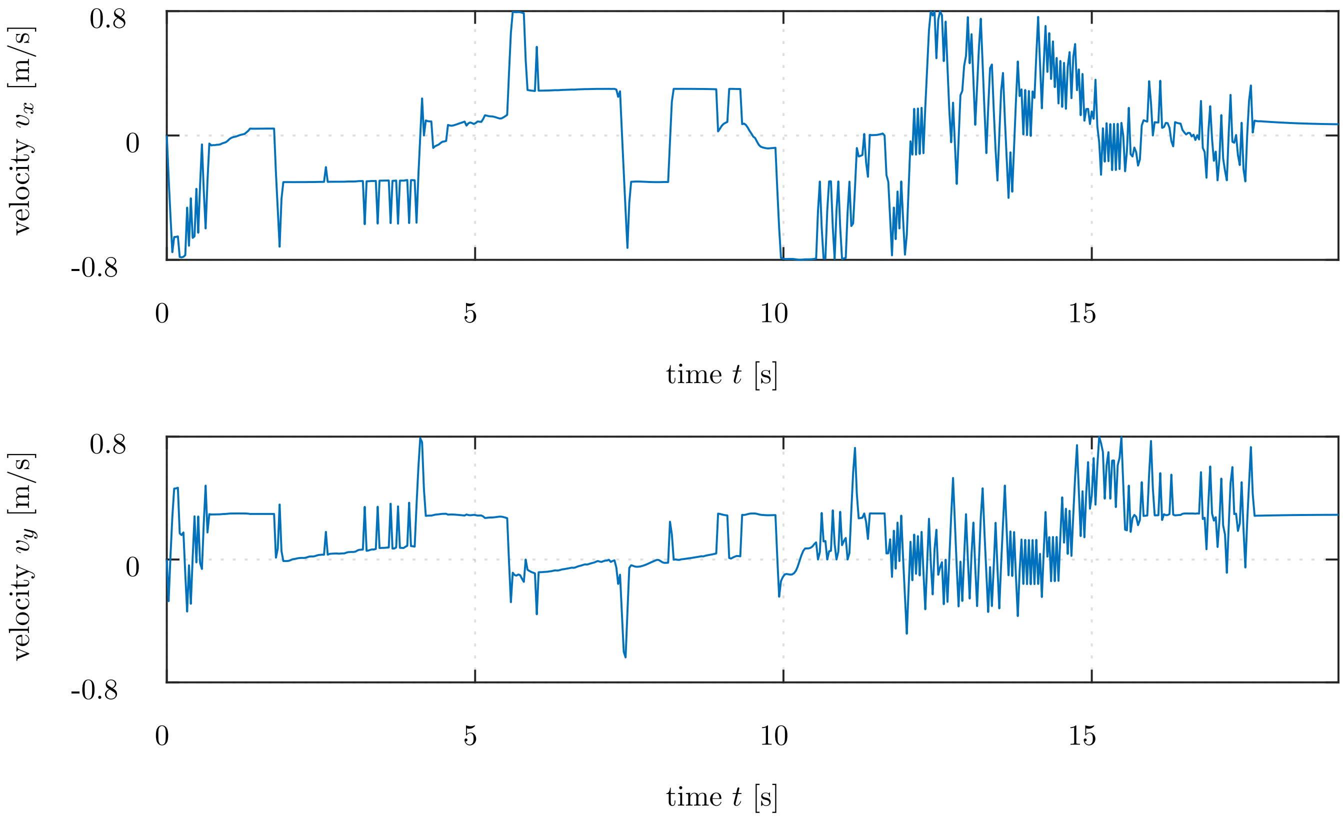


Fig. 6: Velocity of the robot located at the left down in Fig5(a).

of the robots in two directions and the robots have less area for maneuvering. Although the location of the obstacles poses a bigger challenge, the robots can transport the plate safely. The last task is to pass through the obstacles shown in Figures 7(m) and 7(n). It can be seen that the robots use all the area available for movement, even a small crack in a non-convex obstacle. Finally, they safely reach the goal without robot-obstacle collisions or the plate falling down.

All things considered, the examined examples shows the devised scheme delivers a very favorable performance. The robots keep the plate stable during the transportation and they can pass through intricate environments. Although in many mechanical contact problems, the slipping acts as an unwanted disturbance, it gives the ability to change the formation under the plate and the robots use the slipping in order to alter the formation shape.

6 Conclusions

In this paper, a novel approach for transporting an elastic plate using only friction and normal forces has been investigated. A linear complementarity problem is solved to calculate the normal forces of the unilateral contacts between the load and the mobile robots. The obstacles are mathematically represented as convex polytopes in order to find a suitable path through an unknown environment. This enables the representation of arbitrary polygonal obstacles. As a next step, the formation control has been investigated as another aspect of this research. The absence of prehensile contact gives the ability to change the formation under the plate. Using this mechanism, a formation control scheme based on a deployment problem has been designed where the desired positions of the robots are the centers of Voronoi cells. To guarantee the stability of the mechanism, stability conditions have been investigated to prevent the plate from falling down. Augmented Lagrangian particle swarm optimization has been employed to solve the optimization problem in a distributed fashion. The overall scheme has been tested

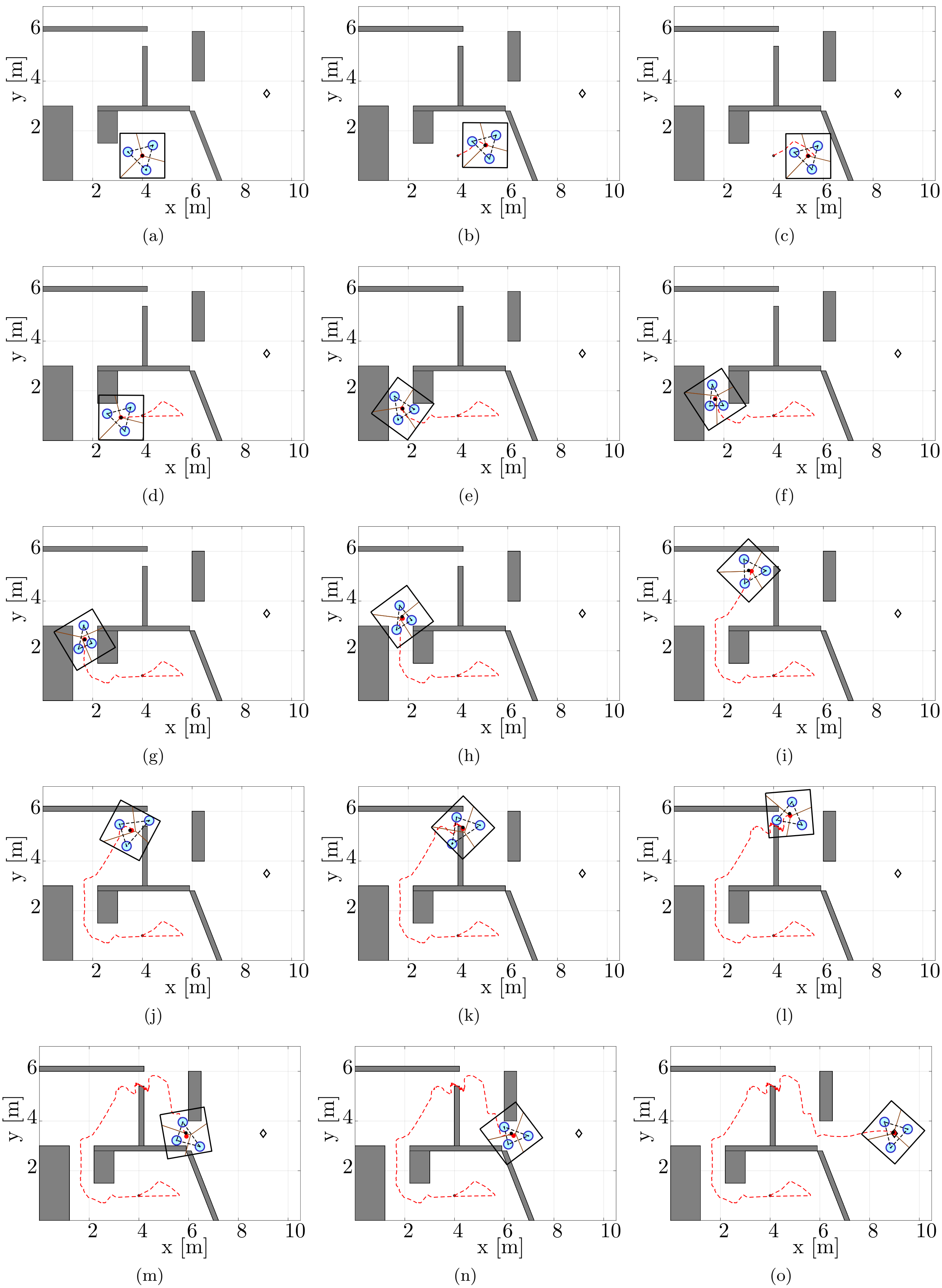


Fig. 7: Plate transportation through an intricate, memorized, unknown environment.

in simulations and the results show that the robots can spread out under the plate properly. Also, the robots can perform intricate maneuvers while they maintain the stability of the plate. Finally, the scheme has been tested in an unknown environment with many obstacles and the simulation results show that the scheme works well also in this example. As the next step of this research, the scheme will be tested on the prepared hardware to investigate the performance of it on the real robots.

Acknowledgements

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References

[1] B.D.O. Anderson, B. Fidan, C. Yu, and D. Walle, Uav formation control: Theory and application, in *Recent Advances in Learning and Control*, London: Springer, 2008.

[2] P. Ögren, M. Egerstedt, and X. Hu, A control Lyapunov function approach to multiagent coordination, *IEEE Transactions on Robotics and Automation*, Vol. 18, no. 5, pp. 847–851, 2002.

[3] Q. Tang and P. Eberhard, Cooperative motion of swarm mobile robots based on particle swarm optimization and multibody system dynamics, *Mechanics Based Design of Structures and Machines*, Vol. 39, no. 2, pp. 179–193, 2011.

[4] R. Groß, F. Mondada, and M. Dorigo, Transport of an object by six pre-attached robots interacting via physical links, in *Proceedings of the 2006 IEEE International Conference on Robotics and Automation*, pp. 1317–1323, Orlando, USA, 2006.

[5] N. Miyata, J. Ota, T. Arai, and H. Asama, Cooperative transport by multiple mobile robots in unknown static environments associated with real-time task assignment, *IEEE Transactions on Robotics and Automation*, Vol. 18, no. 5, pp. 769–780, 2002.

[6] K.M. Lynch, Nonprehensile robotic manipulation: Controllability and planning, PhD Thesis, Robotics Institute, Carnegie Mellon University, 1996.

[7] J. Chen, M. Gauci, W. Li, A. Kolling, and R. Groß, Occlusion-based cooperative transport with a swarm of miniature mobile robots, *IEEE Transactions on Robotics*, Vol. 31, no. 2, pp. 307–321, 2015.

[8] E. Sharafian Ardakani, H. Ebel, and P. Eberhard, Transporting an elastic plate using a group of swarm mobile robots, in *Proceedings of the IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*, pp. 1393–1398, Munich, Germany, 2017.

[9] H. Ebel, E. Sharafian Ardakani, and P. Eberhard, Distributed model predictive formation control with discretization-free path planning for transporting a load, *Robotics and Autonomous Systems*, Vol. 96, pp. 211–223, 2017.

[10] H. Ebel, E. Sharafian Ardakani, and P. Eberhard, Comparison of distributed model predictive control approaches for transporting a load by a formation of mobile robots, in *Proceedings of the 8th ECCOMAS Thematic Conference on Multibody Dynamics*, pp. 1393–1398, Prague, Czech Republic, 2017.

[11] G.L. Mariottini, F. Morbidi, D. Prattichizzo, G.J. Pappas, and K. Daniilidis, Leader-follower formations: Uncalibrated vision-based localization and control, in *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 2403–2408, Rome, Italy, 2007.

[12] J. Chen, D. Sun, J. Yang, and H. Chen, A leader-follower formation control of multiple nonholonomic mobile robots incorporating receding-horizon scheme, *The International Journal of Robotics Research*, Vol. 29, no. 6, pp. 727–747, 2009.

[13] V. Gazi, Swarm aggregations using artificial potentials and sliding-mode control, *IEEE Transactions on Robotics*, Vol. 21, no. 6, pp. 1208–1214, 2005.

[14] W. Ren and R. Beard, Decentralized scheme for spacecraft formation flying via the virtual structure approach, *Journal of Guidance, Control, and Dynamics*, Vol. 27, no. 1, pp. 73–82, 2004.

[15] T. Balch and R. C. Arkin, Behavior-based formation control for multirobot teams, *IEEE Transactions on Robotics and Automation*, Vol. 14, no. 6, pp. 926–939, 1998.

[16] M. Mesbahi and M. Egerstedt, *Graph Theoretic Methods in Multiagent Networks.* Princeton: Princeton University Press, 2010.

[17] Z. Peng, G. Wen, A. Rahmani, and Y. Yu, Distributed consensus-based formation control for multiple nonholonomic mobile robots with a specified reference trajectory, *International Journal of Systems Science*, Vol. 46, no. 8, pp. 1447–1457, 2015.

[18] K. Sedlaczek and P. Eberhard, Using augmented Lagrangian particle swarm optimization for unconstrained problems in engineering, *Structural and Multidisciplinary Optimization*, Vol. 32, no. 4, pp. 277–286, 2006.

[19] M. Bliesener, C. Weber, K. Kling, U. Karras, and D. Zitzmann, *Festo Robotino Manual.* Festo Didactic GmbH & Co. KG, Denkendorf, Germany, 2007.

[20] C. Makkar, W.E. Dixon, W.G. Sawyer, and G. Hu, A new continuously differentiable friction model for control systems design, in *Proceedings of the IEEE/ASME International Conference on Advanced Intelligent Mechatronics*, pp. 600–605, Monterey, USA, 2005.

[21] E.W. Dijkstra, A note on two problems in connexion with graphs, *Numerische Mathematik*, Vol. 1, no. 1, pp. 269–271, 1959.