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Cooperative Rendezvous and Docking for Underwater Robots using Model Predictive Control and Dual Decomposition

Mikkel Cornelius Nielsen¹,², Tor Arne Johansen¹, Mogens Blanke¹,²

Abstract—This paper considers the problem of rendezvous and docking with visual constraints in the context of underwater robots with camera-based navigation. The objective is the convergence of the vehicles to a common point while maintaining visual contact. The proposed solution includes the design of a distributed model predictive controller based on dual decomposition, which allows for optimization in a decentralized fashion. The proposed distributed controller enables rendezvous and docking between vehicles while maintaining visual contact.

I. INTRODUCTION

Intervention, maintenance, and repair (IMR) operations are an increasingly critical area of application in the offshore industry. Deployment of future sub-sea production facilities is anticipated to occur in deeper and more remote locations. The increased depth requires more frequent maintenance, which is already a complicated task at places not directly accessible by humans. The offshore IMR operations are typically carried out by Remotely-Operated-Vehicles (ROVs). The vision of the complete autonomy in the future has increased the interest in Autonomous-Underwater-Vehicles with intervention capabilities (I-AUVs). Multiple recent projects have considered persistent autonomy for intervention-type marine vehicles.

The FP7 project PANDORA investigated the problem of physical intervention between underwater vehicles and underwater panels [16], [20]. The TRITON project investigated docking and manipulation between underwater vehicles and stationary facilities [21], [22]. Operating near exposed offshore structures involves considerable risk [32], [31]. The NextGenIMR project considered the mitigation of operational risk in autonomous interventions such as probability of mission success in case of degradation of the AUV during an active mission combined with shared control with human supervisors [29], [28]. Extending the autonomy to multiple I-AUVs could potentially allow for more flexible and fault-tolerant operations [7], [11]. Multi-vehicle systems with interaction capabilities would allow for smaller vehicles with more specialized tasks such as data-muling, transportation of tools, or collection of test samples [33]. In each case, the vehicles would have to rendezvous to make the exchange while possibly solving another objective — such as structural monitoring — simultaneously.

Rendezvous and docking are not novel concepts, and multiple authors have considered docking for AUVs. However, the most classic examples are under-actuated torpedo type vehicles [2], [6] and [19], whereas the most common types of IMR vehicles are bulky and fully-actuated [4], [27]. The aeronautical literature has investigated rendezvous and docking for spacecrafts [17], [18], [24], [23], but does not consider damping forces due to the low drag coefficient of the thermospheric layer.

The issue of multi-vehicle rendezvous and docking with multiple objectives, input constraints, and visual constraints pose a challenging problem. Model Predictive Control (MPC) is an advanced control strategy often employed to solve problems where constraints pose a central issue in the objectives. Several authors, [5], [8], [12], have investigated distributed MPCs (DMPCs). Dual decomposition is a frequently applied method, which decomposes a large central optimization problem into smaller sub-problems that can be solved locally.

The decomposition transforms the coupled objective function into decoupled objective functions with coupling constraints. Afterwards, the constraints are relaxed using Lagrangian relaxation and the individual vehicles enforce the coupling constraints by manipulation of the dual variables. Multiple authors, [9], [26], [14], [10], have exploited the dual decomposition technique in various contexts. However, none have considered multi-vehicle docking.

This paper proposes a new multi-vehicle docking control strategy. The strategy utilizes a DMPC by dual decomposition to achieve rendezvous while the vehicles maintain visual contact with each other. The rendezvous problem is solved as a consensus problem solved by introducing a consensus point with a coupled equality constraint between the vehicles. Inspired by, [24] and [23], the visual constraint of the cameras are constructed as inequalities. The constraints are decomposed using dual decomposition and subsequently relaxed by Lagrangian relaxation. The dual variables are then updated by negotiation between neighboring vehicles to thereby enforce the relaxed constraints.

The organization of this paper is as follows: Section II describes the model dynamics used in the paper. Then the overall problem is presented in a centralized fashion in Section III. In Section IV the distributed controller is derived from the centralized problem using dual decomposition. Section V presents and discusses the results of the simulation.
Finally, Section VI draws the conclusion along with possible
future extensions of the study.

II. MODELING

This section starts by an assumption made to reduce problem
to a planar case. The dive-plane is stabilized by an active
attitude and heave control system. The vehicle considered in
this paper is a horizontal plane model of three degrees-of-
freedom (DOF). Two coordinate frames are considered, first
the global navigation frame denoted by \( \{ n \} \) is approximated
by a local earth-fixed North-East plane and secondly body-
fixed frames attached to each of the vehicles such that the
frames are aligned with the principle axes. The pose of a
vehicle in the global frame is denoted \( \eta \) is defined as follows:

\[
\eta = [N, E, \psi]^T,
\]

where \( N \) and \( E \) are the position coordinates in the North-
East frame and \( \psi \) is the yaw-angle relative to north. The
body-fixed velocity vector is denoted \( \nu \) and defined as:

\[
\nu = [u, v, r]^T,
\]

where \( u \) is the surge velocity along the longitudinal \( x \)-axis,
\( v \) is the sway velocity along the lateral \( y \)-axis and \( r \) is the
rotation velocity around the local downward pointing axis
\( x \times y \). The transformation matrix \( J_\psi \) defines the kinematic
relationship between body-fixed and global frame velocities
as follows:

\[
\dot{\eta} = \begin{bmatrix}
\cos(\psi) & -\sin(\psi) & 0 \\
\sin(\psi) & \cos(\psi) & 0 \\
0 & 0 & 1
\end{bmatrix} \nu.
\]

Fig. 1 shows the global coordinate frame with the origin
denoted \( O_n \) along with the two coordinate frames attached
to two vehicles.

A. Kinetics

Underwater vehicles are affected by hydrodynamic effects.
As a consequence a vehicle experiences the effect of hydro-
dynamic damping and added mass.

\[
M \dot{\nu} + D(\nu) \nu = u,
\]

where \( M \) and \( D \) are the inertia and damping matrix,
respectively, and defined as,

\[
M \triangleq \text{diag}(m_{11}, m_{22}, m_{33}), \quad D \triangleq \text{diag}(d_{11}, d_{22}, d_{33}),
\]

and \( u \) being the force input in each DOF. The model Eq. (3)
and (4) is represented on standard Ordinary-Differential-
Equation (ODE) form by aggregating the pose and body-
velocity vector as follows:

\[
x = [\eta^T, \nu^T]^T.
\]

The combined state evolution can then be written as follows:

\[
\dot{x} = f(x, u).
\]

When considering multiple vehicles in Section III, the ve-
hicles associated with the \( i \)-th vehicle is assigned an index
\( i \).

III. MULTI-VEHICLE MODEL PREDICTIVE CONTROL FOR
DOCKING

This section defines the consensus and visual constraint, as
well as, the centralized MPC controller. Two objectives,
consensus and visual constraints, are defined and combined
into a centralized controller.

A. Notation

Consider a multi-vehicle system comprised of \( n \) agents.
The agents interact through a network defined by a graph-
topology \( G \). Agent \( i \) in the network correspond to a vertex \( v_i \)
in the graph, the connection between individual agents are
defined by the edge \( e_{ij} = v_iv_j \). Together the set of vertices
\( V \) and the set of edges \( E \) constitute a graph \( G \).

\[
G = \{ V, E \}.
\]

Each agent in the graph has a set of neighbors \( N_i \) consisting
of all vertices in the graph connected to the agent

\[
N_i(G) = \{ v_j \in V \mid v_iv_j \in E \vee v_jv_i \in E \}.
\]

The graph \( G \) in this paper is un-directed. However, the
notational convenience, an arbitrary direction is assigned.
Thereby there exist a set of predecessors and successors for
each vertex,

\[
N_i^+(G) = \{ v_j \in V \mid v_iv_j \in E \},
\]

\[
N_i^-(G) = \{ v_j \in V \mid v_jv_i \in E \},
\]

such that \( N_i = N_i^+ \cup N_i^- \).

B. Line-of-Sight Constraints

To utilize visual navigation between vehicles, it is necessary
to restrict the motion between them such that they never
loose esight of each other. Inspired by work in [23], [24],
and [25], the line-of-sight (LOS) constraints can be formu-
lated as follows:

\[
\begin{align*}
\mathbf{n}_{i,j}^+ &\leq 0, \quad \forall v_i \in V \wedge v_j \in N_i, \\
\mathbf{n}_{i,j}^- &\leq 0, \quad \forall v_i \in V \wedge v_j \in N_i,
\end{align*}
\]

where the normal vectors \( \mathbf{n}_{i,j}^+ \) and \( \mathbf{n}_{i,j}^- \) are parameterized in
the \( i \)th vehicles respective camera rotation. Notice, that the
\( \mathbf{n} \) vectors are parameterized in the states, and thus are
time-varying. The \( e_{j,i} \) is the relative position between the vehicle
in the global frame and is assumed measured by the local
camera.

\[
e_{j,i} = [N_j - N_i, E_j - E_i]^T.
\]
docking requires physical contact. Introducing the vectors will converge from a direction defined by the camera cones. Practice since the vehicles cannot occupy the same space, meaning the vehicles should converge to and remain at a common point.

The control objective is to solve the rendezvous problem, C. Consensus Problem

The parameterizations of the normal vectors \( \mathbf{n}_{i,j}^+ \) and \( \mathbf{n}_{i,j}^- \) are:

\[
\mathbf{n}_{i,j}^+: \left[ -\sin \left( \xi_{i,k} + \alpha_k \right), \cos \left( \xi_{i,k} + \alpha_k \right) \right], \\
\mathbf{n}_{i,j}^-: \left[ \sin \left( \xi_{i,k} - \alpha_k \right), -\cos \left( \xi_{i,k} - \alpha_k \right) \right],
\]

where \( \alpha_k \) is the camera half-angle of the visual cone for camera \( k \), \( \xi_{i,k} \) is the direction of the cone relative to the global frame \( \xi_{i,k} = \psi_i + \phi_k \) with \( \phi_k \) being the relative rotation between the vehicle \( i \)'s local x-axis and the visual cone of camera \( k \). Fig. 1 shows the camera cone of two vehicles with respect to each other and a target.

C. Consensus Problem

The control objective is to solve the rendezvous problem, meaning the vehicles should converge to and remain at a common point.

\[
\lim_{t \to \infty} \| \mathbf{\eta}_i - \mathbf{\eta}_j \| = 0 \quad \forall v_i \in \mathcal{V} \land \ \forall v_j \in \mathcal{N}_i, \tag{14}
\]

\[
\lim_{t \to \infty} \| \mathbf{\nu}_i \| = 0 \quad \forall v_i \in \mathcal{V}. \tag{15}
\]

The rendezvous objective of Eq. (14) is not feasible in practice since the vehicles cannot occupy the same space, however, in combination with the visual constraint the system will converge from a direction defined by the camera cones. Thus the vehicles will collide, but this is the desire as docking requires physical contact. Introducing the vectors \( x, \eta, \nu \) and \( u \) as follows:

\[
\eta = [\eta_1^T, \ldots, \eta_n^T]^T, \quad u = [u_1^T, \ldots, u_n^T]^T, \\
\nu = [\nu_1^T, \ldots, \nu_n^T]^T, \quad x = [x_1^T, \ldots, x_n^T]^T,
\]

where the subscript \( \eta_i \) denotes the pose of vehicle \( v_i \). The objective function \( J \) of the centralized problem is formulated as follows,

\[
J(\mathbf{X}, \mathbf{U}) = \sum_{k=0}^{N-1} l(\mathbf{x}_{t+k|i}, \mathbf{u}_{t+k}), \tag{16}
\]

where \( \mathbf{U} \) is all control inputs for all vehicles across the time horizon \( \mathbf{U} = [\mathbf{u}_1, \mathbf{u}_{k+1}, \ldots, \mathbf{u}_{n,N}] \). \( \mathbf{X} \) is the control horizon, \( \mathbf{X} \) is all the state-vectors over the horizon, and the function \( l(\mathbf{x}, \mathbf{u}) \) is defined as:

\[
l(\mathbf{x}, \mathbf{u}) = \mathbf{\eta}^T(\mathbf{L} \otimes \mathbf{P})\mathbf{\eta} + \mathbf{\nu}^T \mathbf{W}\mathbf{\nu} + \mathbf{u}^T \mathbf{R}\mathbf{u}, \tag{17}
\]

where matrix \( \mathbf{L} \) is the Laplacian matrix of the graph, \( \otimes \) is the Kronecker product, \( \mathbf{P}, \mathbf{W} \) and \( \mathbf{R} \) are tuning matrices.

D. Centralized Problem

The centralized control problem is composed of the consensus problem and the LOS constraints. The overall controller is formulated as follows:

\[
\begin{align*}
\text{minimize} \quad & J(\mathbf{X}, \mathbf{U}) \tag{18} \\
n\text{s.t.} \quad & \mathbf{u}_{i,t+k} \in \mathcal{U}_i, \ \forall v_i \in \mathcal{V}, \\
& \mathbf{x}_{i,t+k+1|t} = f(\mathbf{x}_{i,t+k|i}, \mathbf{u}_{i,t+k}), \ \forall v_i \in \mathcal{V}, \\
& \mathbf{n}_{i,j}^T \mathbf{e}_{i,j} \leq 0, \ \forall v_i \in \mathcal{V} \land \ \forall v_j \in \mathcal{N}_i, \\
& \mathbf{x}_{i+k|t} = [\mathbf{x}_{1,t+k|i}, \mathbf{x}_{2,t+k|i}, \ldots, \mathbf{x}_{n,t+k|i}], \\
& \mathbf{u}_{i+k} = [\mathbf{u}_{i,t+k}, \mathbf{u}_{i,t+k+1}, \ldots, \mathbf{u}_{i,t+k+K}],
\end{align*}
\]

where \( \mathcal{U}_i \) is the input constraints for vehicle \( v_i \).

IV. COOPERATIVE MODEL PREDICTIVE CONTROL

The controller must be converted into a distributed formulation to effectively employ it in a multi-vehicle system. This section describes the usage of dual decomposition to distribute the problem among the agents.

A. Rendezvous Problem

The rendezvous problem from Sec. III-C is solved purely through the objective function in Eq. (18). However, the function itself relies on the difference in the pose of the vehicles due to \( \mathbf{L} \). Hence the objective function is not separable. Introducing a new consensus parameter vector \( \mathbf{\theta} \in \mathbb{R}^3 \), which acts as a universal rendezvous point for the system, allows for the reformulation of the objective function. The global rendezvous point \( \mathbf{\theta} \) is then distributed by introducing a local version \( \mathbf{\theta}_i \) on each vehicle and adding the equality constraints as follows,

\[
\mathbf{\theta}_i = \mathbf{\theta}_j, \quad \forall v_i \in \mathcal{V} \land \ \forall v_j \in \mathcal{N}_i. \tag{20}
\]
The stage cost function of Eq. 17 is reformulated into the following expression:

\[ l_i(x_i, u_i, \theta_i) = (\eta_i - \theta_i)^T P(\eta_i - \theta_i) + \nu_i^T W \nu_i + u_i^T R u_i. \]  

(21)

The Hessian of \( l_i \) is only positive-semidefinite, and thus the problem is under-specified. There is no guarantee that the consensus point reaches a steady point unless additional pose constraints are applied, such as a stationary target or target area. The equality constraint of Eq. (20) is subsequently softened using Lagrangian relaxation and added to the objective function in the following section.

B. LOS-Constraint

The LOS constraints of Eq. (12) depends on the position error \( e_{j,i} \) and the normal vectors are parameterized in the attitude of the local vehicle.

\[
\begin{align*}
    n_{i,j}^T p_j - n_{i,j}^T p_i &\le 0, \\
    n_{i,j}^T p_j - n_{i,j}^T p_i &\le 0.
\end{align*}
\]

(22)

Together, the constraints can be reformulated on matrix form as follows,

\[ A_{i,j} x_j - A_{i,j} x_i \le 0. \]

(23)

Finally, since the constraint is now linear in the state, a local optimization problem can be formulated,

\[
\begin{align*}
    J_i(X_i, U_i, \Theta_i) &= \sum_{k=0}^{N-1} l(x_{i,t+k|i}, u_{i,t+k}) \\
    &+ \sum_{j \in N_i} \left[ e_{j,i}^T A_{i,j} - \lambda_{i,j,t}^T A_{i,j} | x_{j,t+k} \right] \\
    &+ \sum_{j \in N_i^c} \mu_{i,j,t}^T \theta_{i,t+k} - \sum_{j \in N_i^c} \mu_{i,j,t}^T \theta_{i,t+k},
\end{align*}
\]

(24)

where \( \lambda_{j,i} \) and \( \mu_{j,i} \) are the Lagrangian multipliers associated with the LOS constraint from vehicle \( j \) to vehicle \( i \) and the consensus equality constraint associated with the edge \( e_{j,i} \) respectively. \( X_i \) is the states of vehicle \( i \) over the time horizon, \( X_i = [x_{i,0}, x_{i,1}, \ldots, x_{i,t+N-1}] \), \( U_i \) is the inputs over the time horizon \( U_i = [u_{i,0}, u_{i,1}, \ldots, u_{i,t+N-1}] \) and \( \Theta_i \) is the locally computed consensus point along the time horizon, \( \Theta_i = [\theta_{i,0}, \theta_{i,1}, \ldots, \theta_{i,t+N-1}] \). The control problem can now be reformulated as a local optimization problem as follows:

\[
\begin{align*}
    \text{minimize} & \quad J_i(X_i, U_i, \Theta_i) \\
    \text{s.t.} & \quad U_i = [u_{i,0}, u_{i,1}, \ldots, u_{i,t+N-1}] \\
    & \quad x_{i,t+k} = f_i(x_{i,t+k-1}, u_{i,t+k}).
\end{align*}
\]

(25)

(26)

The dual variables \( \lambda \) for the visual inequalities are updated using the projected sub-gradient method [3] as follows:

\[
\begin{align*}
    \lambda_{i,j,t}^{r+1} &= \lambda_{i,j,t}^r + \gamma_{i,j}^r \left( A_{i,j,t+k} [x_{i,t+k}^r - x_{i,t+k}^r] \right) + ,
\end{align*}
\]

(27)

where \( (\cdot)^r \) are the resulting optimal values from the solution to Eq. (25-26), \( (\cdot)^+ \) denotes the rth iteration, \((\cdot)_{++} \) is the projected gradient, and \( A_{i,j,t+k} \) is the visual constraint matrix updated over the time horizon.

The dual variables \( \mu \) for the consensus equality constraints are likewise updated using the sub-gradient method [3].

\[
\mu_{i,j,t+k}^{r+1} = \mu_{i,j,t+k}^r + \gamma_{i,j}^r (\theta_{i,t+k}^r - \theta_{i,t+k}^r).
\]

(28)

The overall control algorithm is shown in Algorithm 1.

Algorithm 1 Distributed Controller

Input: \( \lambda^0, \mu^0 \)

1: for \( r = 0, \ldots, L - 1 \) do
2: \quad Solve local optimization problem Eq. (25) to obtain \( X_i^r, U_i^r \) and \( \Theta_i^r \)
3: \quad Communicate the local state trajectories \( X_i^r \) and consensus point sequence \( \Theta_i^r \) to neighbors in \( N_i \).
4: \quad Compute the new price sequences \( \lambda^{r+1} \) and \( \mu^{r+1} \)
5: \quad Update the control sequence \( U_i^{r+1} \) locally by applying Eq. (27) and (28)
6: end for
7: Apply first element of the control sequence \( U_i^{L-1} \) to the local plant.

V. SIMULATIONS

In this section a simulation is conducted to show the application of the controller. The simulation is implemented in Python using CasADI [1]. The model of Eq. (7) is discretized using Runge-Kutta4. The applied optimization solver is the interior-point implementation IPOPT [34].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_{i,j} )</td>
<td>30 ( [0, 100] )</td>
<td></td>
</tr>
<tr>
<td>( \gamma_{i,j} )</td>
<td>2 ( [0, 10] )</td>
<td></td>
</tr>
<tr>
<td>( D_i )</td>
<td>diag((0, 30, 1) )</td>
<td></td>
</tr>
<tr>
<td>( M_i )</td>
<td>diag((10, 10, 1) )</td>
<td></td>
</tr>
<tr>
<td>( \Theta )</td>
<td>diag((0, 0, 0, 0, 0, 0) )</td>
<td></td>
</tr>
<tr>
<td>( L )</td>
<td>15 | |</td>
<td></td>
</tr>
<tr>
<td>( p_{i,0} )</td>
<td>[-1, 2, -0.5, 0, 0, 0] |</td>
<td></td>
</tr>
<tr>
<td>( p_{i,0} )</td>
<td>[-1, 2, -0.5, 0, 0, 0] |</td>
<td></td>
</tr>
<tr>
<td>( O_A )</td>
<td>diag((6, 1, 2) )</td>
<td></td>
</tr>
<tr>
<td>( d_{max} )</td>
<td>[10, 10, 10, 10, 10, 10] |</td>
<td></td>
</tr>
<tr>
<td>( N )</td>
<td>30 |</td>
<td></td>
</tr>
<tr>
<td>( a_k )</td>
<td>25 ( [deg] )</td>
<td></td>
</tr>
<tr>
<td>( b )</td>
<td>0.05 ( [s] )</td>
<td></td>
</tr>
</tbody>
</table>

TABLE I: Parameters and initial conditions used in the simulation scenario.

A. Monitoring and Rendezvous

The simulation scenario consists of two vehicles \( v_1 \) and \( v_2 \) and a stationary target \( O_A \). Vehicle \( v_1 \) is inspecting target \( O_A \), while at the same time rendezvous and docking with vehicle \( v_2 \). The inspecting vehicle is required to stay within
In this paper, we presented a distributed model predictive controller for the solution to a cooperative rendezvous and docking problem under visual camera constraints. The problem consisted of two subparts, namely a consensus problem and a visual field-of-view restriction. A DMPC was derived using dual decomposition. A simulation study was conducted to show the application of the controller, where two vehicles conduct are rendezvous and docking maneuver while one of the vehicles stay within a maximum prescribed distance of a designated target and maintain visual contact.

The present communication technology does allow the proposed method to work, but for robustness reduction in communication is a topic of future research.