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Hybrid Predictive Control for Aerial Robotic Physical Interaction towards Inspection Operations

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Abstract—The challenge of aerial robotic physical interaction towards inspection of infrastructure facilities through contact is the main motivation of this paper. A hybrid model predictive control framework is proposed, based on which a typical quadrotor vehicle becomes capable of stable physical interaction, accurate trajectory tracking on environmental surfaces as well as force control with only minor structural adaptations. Convex optimization techniques enabled the explicit computation of such a controller which accounts for the dynamics in free-flight and during physical interaction, ensures the stability of the hybrid system as well as response optimality, while respecting system constraints and imposed logical rules. This control framework is further extended to include obstacle avoidance capabilities. Extensive experimental studies that included complex “aerial-writing” tasks, interaction with non-planar and textured surfaces and obstacle avoidance maneuvers, indicate the efficiency of the approach and the potential capabilities of such aerial robotic physically interacting operations.

I. INTRODUCTION

Miniature Aerial Vehicles (MAVs) have proven to be a highly efficient class of systems with great potential on inspection operations. Utilizing vision, LiDARs or other sensing devices, MAVs are capable of executing complex remote aerial inspection tasks. However, infrastructure inspection operations are not limited to remote sensing but often require physical contact too. Due to this fact and further motivations, several research groups [1–4] have focused on addressing the problem of aerial physical interaction. This work proposes a control framework that provides advanced robotic physical interaction capabilities with only minor structural adaptations of the vehicle.

As shown in Figure 1, a typical quadrotor vehicle is utilized with the only mechanical adaptation being the integration of a simple rigid docking mechanism. The dynamics of the aerial robot are modeled during free-flight as well as during physical interaction and a global model is assembled employing the theory of hybrid automata and their equivalent translation to piecewise affine (PWA) systems. Based on the great breakthroughs in the field of convex optimization, the derived hybrid model becomes the basis for the computation of a powerful explicit hybrid model predictive control law (hybrid MPC). This controller provides a set of key features that are of critical importance for the field of aerial contact-based inspection and physical interaction in general. Most importantly, it ensures stable transitioning between free-flight and physical contact and achieves response optimality while satisfying the modeled system constraints and imposed mission-related logical rules. Consequently, accurate in-contact trajectory tracking is achieved along with force control capabilities. Furthermore, this control framework is extended to include means of obstacle avoidance. Being explicitly computed, it allows for fast real-time execution.

Fig. 1. Aerial robotic physical interaction experiments.

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The properties of the controlled system were evaluated experimentally. Mounting a marker on the vehicle, a wide set of “aerial-writing” operations were conducted in order to evaluate the capabilities of aerial physical interaction and inspection through contact. Such an “aerial-writing” task may be considered similar to that of non-destructive testing (NDT) of infrastructure using ultrasound probes. Despite the constraints imposed from the environment and the underactuated nature of the vehicle dynamics, sufficiently accurate in-contact trajectory tracking and force control was achieved. Moreover, the capacity for achieving smooth approaching and docking maneuvers even subject to temporal faults of the position localization subsystem was evaluated. Finally, the capabilities of obstacle avoidance are presented.

This paper is structured as follows. In Section II, the hybrid model of the system dynamics is presented, followed by the development of the hybrid model predictive controller
in Section III. Extended experimental studies are presented in Section IV, while conclusions are drawn in Section V.

II. HYBRID MODELING

The utilized “ASLquad” is a quadrotor aerial robot that adopts an in-house airframe development, the electronic and actuation components of an AscTeC Hummingbird and a modular software framework. The airframe has an arm length \( l_a = 0.3 \text{m} \) and a docking mechanism has been mounted on its front and back side to ensure a safe physical interaction. Such a mechanism corresponds to the only required structural modification to any multicopter, so that similar aerial physical interaction tasks become possible. On the front side, a marker is mounted so that writing tasks are executed and visually verified. The overall mass is \( m = 0.65 \text{kg} \).

A. Attitude Dynamics Identification

An attitude controller was already implemented for this vehicle. The choice of not designing a specialized attitude controller was motivated by the fact that nowadays, a huge market of multicopters and other unmanned rotorcrafts exists with such a low-level controller already integrated. As long as physical interaction tasks can be executed safely and accurately by only adapting the high-level controller, the choice of redesigning the attitude loop was considered unjustified. Therefore, each of the modes of every hybrid automaton: the forward–motion longitudinal dynamics that are constrained in a bounded set \( u_F \in \mathbb{R}^3 \times \mathcal{L}_F \rightarrow \mathcal{L} \), the lateral and altitude dynamics which are both affected by friction once contact is established. Consequently, a Domain Map is defined for the continuous states of each of the modes of every hybrid automaton:

\[
\mathcal{D}_F(FF) : \mathbb{R}^3 \times \mathcal{L}_F, \quad \mathcal{D}_F(PI) : \mathcal{R}^3 \times \mathcal{L}_F
\]

A locally Lipschitz Flow Map \( f(x_\mathcal{L}, \mathcal{D}_F) \) acts on these domain maps and describes the continuous evolution of the states for every operative mode. Each of the flow maps consists of two components \( f(x_\mathcal{L}, \mathcal{D}_F(FF)), f(x_\mathcal{L}, \mathcal{D}_F(PI)) \) for the free–flight and physical interaction modes respectively. The following state–space representations describe the evolution of the longitudinal dynamics:

\[
\begin{align*}
\dot{x}_\mathcal{L} & = A^{FF}_\mathcal{L} x_\mathcal{L} + B^{FF}_\mathcal{L} u_\mathcal{L} \\
\dot{x}_\mathcal{L} & = A^{PI}_\mathcal{L} x_\mathcal{L} + B^{PI}_\mathcal{L} u_\mathcal{L} + C^{PI}_\mathcal{L} F_E
\end{align*}
\]

where,

\[
A^{FF}_\mathcal{L} = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & -A^{FF}_F & -g & 0 \\
0 & 0 & 0 & 1 \\
0 & -b_{\phi, \phi} & -b_{\theta, \theta} & 0
\end{bmatrix}, \quad B^{FF}_\mathcal{L} = \begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix}
\]

\[
A^{PI}_\mathcal{L} = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 \\
0 & 0 & -b_{\phi, \phi} & -b_{\theta, \theta}
\end{bmatrix}, \quad B^{PI}_\mathcal{L} = \begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix}, \quad C^{PI}_\mathcal{L} = \begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix}, \quad F_E = \begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix}
\]

and \( F_E \) is the force exerted from the environment and under rigid–body assumptions is equal and opposite to the projected forces.
force on the x-axis \((F_x = -F_s, F_z = -T \sin \theta)\) during stable contact. As shown, the flow map during physical interaction encodes the fact that the system is physically constrained in the forward direction. The lever arm \(l_p = l_p \sin(\beta - \theta)\), \((\beta = 0.14 \text{rad})\), is approximated for \(\theta = -0.035 \text{rad} which corresponds to a typical docking angle, while the longitudinal position \(x\) is defined as the distance of the vehicle CoG to the closest surface of the environment minus the distance of the CoG to the contact point and is considered negative in free–flight and zero during contact \((x \in (-\infty, 0))\). The output vector is set as \(y_{out} = [x, \dot{x}, \theta, \phi, \dot{\theta}, \dot{\phi}]^T\). The lever arm \(l_p\) is the reference thrust signal. Again the adapted \(\lambda^*\) can be approximated for \(f = 14 \text{rad}\), is approximated for \(f = 14 \text{rad}\) and \(f = 0\). The possible mode switchings are represented using the Set of Edges \(E\) as visualized in Figure 2. Since the vehicle may encounter elastic collisions, a rebound loop is added to the hybrid system \(\{FF, FF\}\). The logic that governs the mode switchings, is encoded in the Guard Map \(G\) (Table I) which identifies the set \(G(q_i, q_j)\) to which the outputs of the system have to belong so that transition from the mode \(q_i \in Q\) to \(q_j \in Q\) may occur. By integrating tactile sensors and combining their data with the state variables, a robust contact detection strategy is engineered. For the lateral and altitude hybrid automata, an auxiliary boolean state is added and switches from 0 to 1 based on the aforementioned longitudinal guard maps in order to trigger mode switching. Value \(\Delta x^\text{min} \to 0^+\) is a close to zero tunable threshold.

Finally, for completeness and simulation reasons, a Reset Map \(R\) is formulated for each hybrid automaton and describes, for every edge \((\{FF, FF\}, \{FF, PI\}, \{PI, FF\})\), the values to which the continuous states \(x_k\) are set during a mode transition. This reset map encodes the jump on the attitude rate and velocity of the vehicle in case of elastic collisions and follows the methodology presented in [6].

These hybrid automata represent a global model of the ASLquad during free–flight and physical interaction. Their implementation was achieved using the HYbrid System DEscription Language (HYSDS) 3.0 [7] which provides a rapid prototyping framework integrated with MATLAB® and the Multiparametric ToolBox (MPT) 3.0 [8].

While hybrid automata provide an intuitive way for modeling, piecwise affine systems are more powerful for numerical control computation. Different hybrid systems representations are however translatable from one to the other with equivalence, in the sense that the same input sequences will lead to identical state trajectories. The equivalent PWA system takes the following form in discrete time:

\[
\begin{align*}
x_k(t+1) &= A^F_{x_f} x_k(t) + B^F_{x_f} u_k(t) + f^F_{x_k}(t) \\
y_k(t) &= C^F_{y_k} x_k(t) + D^F_{y_k} u_k(t)
\end{align*}
\]

where \(i(k)\) indicates which hybrid mode (PWA model) is active and the switching rule is now represented in a matrix inequalities form based on the states and inputs vectors:

\[
\begin{align*}
H^F_{x_k} x_k(t) + J^F_{x_k} u_k(t) &\leq K^F_{x_k} \\
H^F_{y_k} x_k(t) + J^F_{y_k} u_k(t) &< K^F_{y_k}
\end{align*}
\]

where the matrices \(A^F_{x_f}, B^F_{x_f}, f^F_{x_k}, C^F_{y_k}, D^F_{y_k}, H^F_{x_k}, J^F_{x_k}, K^F_{x_k}, H^F_{y_k}, J^F_{y_k}, K^F_{y_k}\) are constant and have suitable dimensions, \(i(k) = 1, \ldots, \mu\), where \(\mu\) is the number of the PWA systems required to express the hybrid system \((\mu = 2)\).

### III. HYBRID MODEL PREDICTIVE CONTROL

The proposed control law exceeds the classical synthesis of MPC–based autopilots [9–12] and provides a set of key features for aerial robotic physical interaction operations. Utilizing the concept of receding horizon control over the hybrid model of the vehicle, it ensures its global stability as well as response optimality, while it also makes use of recent advancements in the field of convex optimization to provide a flexible framework that can incorporate artificially imposed mission–related logical rules together with the system state and input constraints. Finally, obstacle avoidance capabilities are incorporated in the same framework. MPT and YALMIP [13] are the main computational tools that enabled the design and explicit computation of such a controller.
A. State and Input Constraints

The following, state and input constraints are imposed in
the optimization process in order to enforce the vehicle’s
operation in a safe subset of its flight envelope:

\[
\begin{align*}
[1_{1,1} & 0_{1,1} & 0_{1,1}] \\
[0_{1,1} & 1_{1,1} & 1_{1,1}] & \\
[0_{1,1} & 1_{1,1} & 1_{1,1}] & \\
[0_{1,1} & 1_{1,1} & 1_{1,1}] & \\
\end{align*}
\leq
\begin{align*}
[1.5\text{m/s} & ] \\
[\pi/4\text{rad} & ] \\
[1.5\text{m/s} & ] \\
[\pi/4\text{rad} & ] \\
[1.5\text{m/s} & ] \\
[\pi/4\text{rad} & ] \\
\end{align*}
\]

B. Imposed Logical Rules

Consequently, a second class of constraints that encode
mission–related logical rules are also imposed. Although
not captured from simple rigid body modeling, the vehicle
has to apply at least a minimum force in order to retain
contact due to the aerodynamic turbulence that occasion-
ally creates repelling forces. Correspondingly, a safety constraint
that enforces a minimum force threshold is imposed during
physical interaction. Moreover, to prevent the vehicle from
tipping over the wall due to the external moments, a tight
hard constraint on the maximum pitch angle is imposed
during contact. These logical rules take the following form:

**IF contact THEN** \( F_y \geq 0.2\text{N} \) (11)

**IF contact THEN** \( \theta \leq \pi/12\text{rad} \) (12)

YALMIP enables the incorporation of these non–convex
logical rules in the optimization.

C. Control Computation

Provided the PWA representations of the hybrid systems
as in (6),(7) as well as the constraints (8),(9),(10) and
the logical rules (11), (12) three hybrid predictive controllers
are computed in a multiparametric fashion [8,14]. Using
a quadratic norm as a metric of optimality and adding
terminal set constraints, the hybrid predictive controller, for
a prediction horizon \( N \), consists of computing the optimal
control sequence \( U_N^n = [u_y(0),...,u_y(N-1)] \) that minimizes
the following objective:

\[
J(x_N,k) = \min_{u_N} \{x_T^A \mathcal{P}_{M \times M} x_N +
\sum_{k=0}^{N-1} x_T^T Q_{M \times M} x_k + u_T^T R_{L \times L} u_k \}
\]

\text{s.t. equation (6),(7),[(8),(9),(10)],[(11),(12)],}\quad x_N,\theta \in T_{set}

where \( \mathcal{P}_{M \times M} \geq 0 \), \( Q_{M \times M} \geq 0 \), \( R_{L \times L} \geq 0 \) are the weighting
matrices of the terminal state, of the states and the manipu-
lated variables respectively and \( T_{set} \) is the terminal set which
is specified as the LQR terminal set in order to guarantee
stability properties [14]. For each subsystem, such a hybrid
MPC is computed based on state feedback. However, for
the purposes of varying force reference, the aforementioned
objective is reformulated in output feedback form.

D. Obstacle Avoidance

The proposed control framework may also be extended
to provide obstacle avoidance capabilities by coupling the
three hybrid automata, modifying the objective function and
adding polyhedral constraints. In an infrastructure inspection
scenario it is very likely that some knowledge of the main
structure is available a priori, which then allows modeling
of most of the obstacles in the workspace. Let \( \mathcal{P}_w \) be a
polyhedron that describes the total workspace of the robot,
\( \mathcal{P}_1, \mathcal{P}_2, ..., \mathcal{P}_p \) polyhedra that enclose the known obstacles
and also provide additional thresholds to account for the
vehicle dimensions and some further safety bounds that allow
limited penetration. The “safe” robot workspace is defined as
the Pontryagin difference \( \mathcal{P}_r = \mathcal{P}_w \setminus \{ \mathcal{P}_1, \mathcal{P}_2, ..., \mathcal{P}_p \} \).
In order to enforce operation within \( \mathcal{P}_r \), the following
adaptation in the optimization problem is required:

\[
\begin{align*}
\min_{u_N} & \quad J(x_N,k) + G_\xi, \text{ if } x_N(k) \in \Pi_k^\xi \\
\text{s.t} & \quad [x, y, z] \in \mathcal{P}_r, \text{ equation (6),(7),(8),(9),(10),(11),(12)}
\end{align*}
\]

where \( \sigma \) indicates that the coupled 3D hybrid automaton
is used. Despite this problem is of increased complexity,
once a explicit solution is computed, its real–time imple-
mentation is very efficient. It is noted that this obstacle
avoidance strategy is not proposed in order to substitute the
need for proper trajectory generation but rather as a last resort
mechanism that ensures the system safety at the control level.

E. Explicit Implementation

One additional important property of the proposed control
strategy is its explicit character. This is a result of the fact
that the control action takes a piecewise affine form [15]:

\[
u_x(k) = F_{\bar{x}} x_k(k) + G_{\bar{x}}, \text{ if } x_k(k) \in \Pi_k^\bar{x}
\]

where \( \Pi_k^\bar{x} \) \( \bar{x} \rightarrow \text{lon, lat, alt or } \sigma \), \( r = 1, ..., N_r \) are the regions
of the receding horizon control strategy. The \( r \)–th control
law is valid if the state vector \( x_{\bar{x}}(k) \) is contained in a
convex polyhedral region \( \Pi_{\bar{x}}^\bar{x} = \{ x_{\bar{x}}(k) | H_{\bar{x}}^\bar{x} x_{\bar{x}}(k) \leq 1 \} \)
computed and described in \( \bar{h} \)–representation during the ex-
licit controller derivation [16]. The controller is equivalently
translated to a mapping between feedback gains and affine
terms \( F_{\bar{x}}, G_{\bar{x}} \) and corresponding polyhedric regions \( \Pi_{\bar{x}}^\bar{x} \). This
explicit controller is equivalent to its online counterpart in the
sense that for identical state trajectories, both produce
the same control actions, and therefore share the same
stabilizing and optimality properties. This fact enables the
seamless real–time implementation of this controller. In
the framework of this work, the real time code is described in
Algorithm 1 and corresponds to an extension of the table
traversal algorithm [16] that also supports multiple inputs.

Finally, in order to compensate for the possibly rotated
yaw angle (\( \psi \)), the derived \( \theta', \phi' \) reference signals are
rotated accordingly.
Algorithm 1: Extended Sequential Table Traversal

**Data:** Regions: $H_r$, $K_r$; Regions feedback laws: $F_{r}$, $G_{r}$; Regions Cost Matrices: $Q_{r}, f_{r}, g_{r}$; Number of regions: $N_r$; Input Penalization Matrix: $R_p$; State: $x(k)$; Previous Optimal Control input: $u_{prev}$

**Result:** Explicit Hybrid MPC control input $u^*_0(x(k))$

$$J_{\text{min}} \leftarrow +\infty$$

$$u_{\text{opt}} \leftarrow u_{\text{prev}}$$

for $r = 1, \ldots, N_r$ do

if $H_r x(k) \leq K_r$ then

$$J_r \leftarrow x(k)^T Q_r x(k) + f_{r}^T x(k) + g_{r}; \quad \text{/* region cost */}$$

$$u_r \leftarrow F_{r} x(k) + G_{r}; \quad \text{/* region control input */}$$

if $J_r < J_{\text{min}}$ then

$$J_{\text{min}} \leftarrow J_r;$$

$$u_{\text{opt}} \leftarrow u_r;$$

else if $J_r = J_{\text{min}}$ then

if $u_r^T R_p u_r \leq u_{\text{opt}}^T R_p u_{\text{opt}}$ then

$$J_{\text{min}} \leftarrow J_r;$$

$$u_{\text{opt}} \leftarrow u_r;$$

end

end

end

$$u^*_0(x(k)) = u_{\text{opt}};$$

IV. EXPERIMENTAL EVALUATION

The efficiency of the proposed control framework was experimentally evaluated. Mounting a marker on the vehicle, a wide set of “aerial–writing” tasks were performed. Such tasks assess the capabilities of aerial contact–based inspection at the control level. Measurements of the thickness of power plant boiler pipes using ultrasound probes corresponds to an indicative example of such applications. Three sets of experiments were conducted, namely a) complex “aerial–writing”, b) sliding on a real segment of boiler pipes also subject to temporal sensor faults and c) obstacle avoidance and docking. In all the conducted experiments position feedback was provided by a Vicon motion capture system, while the onboard inertial measurement unit provided the attitude estimates. The sampling time was set to $T_s = 0.02s$ and $N = 10$. The $x$ reference is always set 5cm behind the environmental surface.

Figure 3 depicts an inspection maneuver that “scans” a prespecified area on a wall with the reference precomputed offline. This, essentially imitates a mission of inspecting the walls of industrial facilities, in order to detect potential damages or developing hazards.

Subsequently, the vehicle was commanded to write a word, and specifically to write “ASL” (acronym of the Autonomous Systems Lab at ETH Zurich). The derived results, shown in Figure 4, present high accuracy compared to the challenging nature of the reference path, the underactuated dynamics of the vehicle and its limited force generation mechanism.

![Figure 3](image1)

**Fig. 3.** Aerial writing experiment, executing a wall inspection through contact path. A recording of this response is available at the video file.

![Figure 4](image2)

**Fig. 4.** Aerial writing of the Autonomous Systems Lab acronym (ASL). A recording of this response is available at the video file.

The next test–case evaluates the physical interaction capabilities on non–planar textured surfaces, as it can be expected in industrial inspection operations. As shown in Figure 5, the robot is commanded to dock and “write” a vertical line on a segment of a real power plant boiler pipe–wall.

![Figure 5](image3)

**Fig. 5.** Vertical sliding on a segment of a real boiler pipe–wall. A video recording of this response is available at the supplementary video file.

During real inspection operations, it may be expected that the position localization subsystem may encounter temporal faults. Such a situation becomes even more challenging if it happens during a docking maneuver. Towards providing a last resort safety mechanism, Figure 6 depicts that a smooth docking maneuver can still be achieved as long as a model...
of sufficient fidelity is available. As shown, for the last 0.4m, the position feedback was based only on forward simulation of the identified dynamics, while once contact is detected the ground truth data were again provided to the system. As illustrated, in such an experiment, the maximum errors are small and the maneuver remains practically unaffected.

Finally, the obstacle avoidance capabilities were evaluated and the results are depicted in Figure 7. With prior knowledge of the obstacle position and dimensions, a bounding polyhedron $\mathcal{P}_o$, is defined and the controller described in Subsection III-D is applied. As demonstrated, a last resort obstacle avoidance mechanism is achieved and ensures the safety of the system.

V. CONCLUSIONS AND FUTURE WORK

A hybrid model predictive control framework that handles the problem of aerial physical interaction and inspection through contact with only minor structural adaptations of the aerial vehicle is proposed. Employing hybrid systems approaches, a global model of the system dynamics in free-flight as well as during physical interaction is derived and becomes the basis for model-based control. The proposed controller ensures the stability of the system and achieves optimal responses while satisfying constraints, imposed logical rules and avoiding obstacles. The efficiency of the proposed method was evaluated using extensive experimental studies that included “aerial–writing” tasks, non–planar and textured surfaces inspection and obstacle avoidance.

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