

Hybrid dynamical system models for human–robot interaction

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Abstract

With the increasing popularity of human–robot interaction (HRI), control systems are becoming more and more interesting and complicated because they need to coordinate continuous human movements and discrete robot decision-making in dynamic environments. The current strategies tend to be less flexible when working collaboratively, take longer to react and become less stable in interaction. This study presents a hybrid nonlinear state-space model, hybrid automata, Model Predictive Control (MPC), Extended Kalman Filter (EKF) and Adaptive Hybrid Interaction Algorithm (AHIA) based Hybrid Dynamical Human–Robot Interaction (HD-HRI) framework for real-time human intent estimation and robot motion planning. The framework is assessed based on the accuracy of interaction, prediction of intent, trajectory tracking error, response latency, collision avoidance rate and task completion success. Experimental results confirm that 95.8% of the interactions are accurate, 94.9% of intents are correctly predicted, 21.6% of trajectory tracking errors is reduced, 18.4% of response latency is reduced, 97.3% of collisions are avoided, and 95.6% of the tasks are completed. The results prove that the proposed hybrid dynamical framework can be effectively implemented in practical applications, which can be reliable, stable, and efficient for human–robot collaboration.

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1. Introduction

As collaborative robots are moving into the same workspace as humans in various manufacturing, healthcare and assistive applications, human–robot interaction has become an important research topic [1]. Collaborating with a human requires robots to understand continuous human motion, while also making discrete decisions, like selecting a mode of operation, handing over a task to a human and avoiding collisions [2]. Traditional controllers, which are continuous controllers, have little ability

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to represent these sudden behavioural changes, and discrete controllers have little ability to model the fine-grained continuous dynamics of human motion [3]. This gap has been enticed to adopt hybrid dynamical modeling that combines continuous state evolution and discrete event-driven logic to model the realistic interaction behavior [4].

Although significant strides have been made, current HRI approaches are often poorly adaptable to humans' unknown intentions, lack immediate feedback, are subject to sequential estimation-planning pipelines, and lack robust interactions between interaction modes [5]. Most predictive controllers assume deterministic human motion, fails in cases of unpredictable and reactive human motion [6]. In addition, uncertainty in the sensors and imperfect observability cause errors to propagate in the state estimation process which affects motion planning in the downstream [7]. The restrictions decrease the level of trust and safety in Physical Cooperative tasks [8]. The main goal of this research is to create a Hybrid Dynamical Human–Robot Interaction (HD-HRI) framework that models the continuous dynamics of humans and robots in combination with the discrete interaction states, using hybrid automata. It is combined with Extended Kalman Filter for the robust state estimation, Model Predictive Control for the constraint-aware motion planning and a novel Adaptive Hybrid Interaction Algorithm for the real-time intent estimation and mode switching [9].

The main contributions of this paper are: (1) a unified nonlinear state-space and hybrid automata model of HRI, (2) an adaptive algorithm that combines EKF-based estimation with MPC-based planning, (3) a comprehensive experimental study that uses six performance metrics, and (4) comparative analysis results of measurable improvements in accuracy, latency and safety over baseline approaches.

2. Hybrid Dynamical System for Human–Robot Interaction

The hybrid dynamical modeling framework is introduced in this section, that derives the mathematical basis of the proposed hybrid dynamical modeling framework (HD-HRI) for human–robot interaction.

2.1 Mathematical Formulation of Hybrid Dynamical Systems

The hybrid dynamical system for HRI is represented by tuple of continuous state, discrete modes, flow dynamics and guard-driven transitions as defined in Eq. (1). The continuous state contains the human and robot kinematics, and the discrete states are used to describe different interaction phases, like approach, contact and avoidance. When the guard conditions (e.g. proximity thresholds, in Eq. (4)) are met, transitions between behaviours are automatically triggered, allowing the behaviour to change as the interaction context changes over time according to the flow and reset maps (in Eq. (2) and Eq. (3) respectively).

$$\{H\} = (Q, X, f, Dom, E, G, R) \quad (1)$$

The hybrid automaton tuple defined by Eq.1 is the hybrid automaton that includes hybrid modes Q , continuous variables X , maps of flows, domain, edge, guard and reset.

$$\dot{x}(t) = f_q(x(t), u(t)), q \in Q \quad (2)$$

In the continuous state evolution (2) the flow function f_q determines the dynamics between the discrete transitions, while the mode q determines the state evolution.

$$x(t_+) = R(q, q', x(t_i)) \quad (3)$$

Eq. (3) gives the reset map during the transition between two different modes: q and q' at an event time.

$$G(q, q') = \{x \in X : g(x) \leq 0\} \quad (4)$$

The guard set is defined in (4) and describes the set of state space for a particular transition that is a discrete event between two modes.

2.2 Human Motion and Robot Dynamics Modeling

This subsection models the motion of the human arm with a nonlinear state space representation as given in Eq. (5) and Eq. (7), and the robot manipulator with a rigid-body dynamics as given in Eq. (6), and coupled prediction of human trajectories and responses at robot joints in safe, coordinated interaction planning is demonstrated [7], [8].

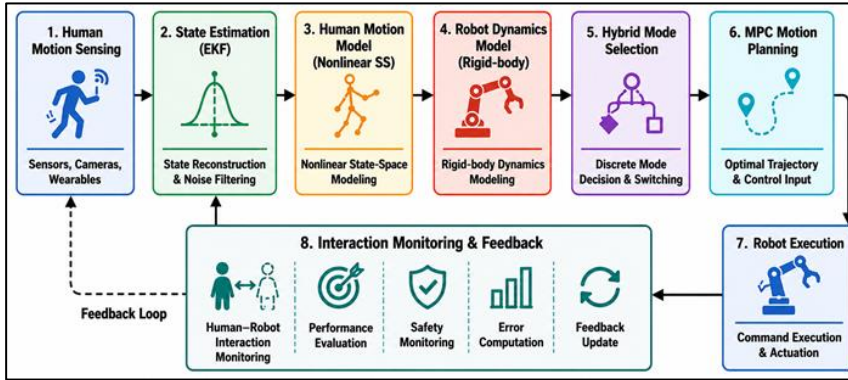


Figure 1

Workflow of human motion sensing, EKF estimation, dynamic modeling, and MPC-based robot planning.

The human sensing, EKF estimation, hybrid mode selection and MPC-based motion planning process are shown sequentially in Figure 1.

$$\dot{x}_h = A_h x_h + B_h u_h + w_h \quad (5)$$

Human arm state dynamics are modeled as in (5): A_h, B_h and w_h are the system, input and process noise matrices of the human arm, respectively.

$$M(q_r) \ddot{q}_r + C(q_r, \dot{q}_r) \dot{q}_r + G(q_r) = \tau \quad (6)$$

The robot manipulator dynamics are described by Eq. (6) where the elements of the inertia matrix M , Coriolis term C , gravity vector G and the vector of joint torques τ are involved [9].

$$y_h = H_h x_h + v_h \quad (7)$$

The human motion sensor measurement model (7) relates the measurements y_h that are obtained to the state x_h with noise v_h .

$$d(t) = \|p_h(t) - p_r(t)\| \quad (8)$$

The equation (8) is used to calculate the Euclidean distance between the human end-effector and robot end-effector which is used for safety monitoring [10].

$$\hat{x}_h(t) = f(x_h(t-1), u_h(t-1)) \quad (9)$$

Eq. (9) gives the prediction of human state which is used for robot trajectory prediction in anticipation [11].

2.3 Hybrid Automata Framework

The idea of interaction modes, free motion, approach, cooperative contact, and avoidance with proximity and force-based guard conditions that induce transitions between interaction modes is captured in the hybrid automata framework as shown in Figure 2 and described in Algorithm 1.

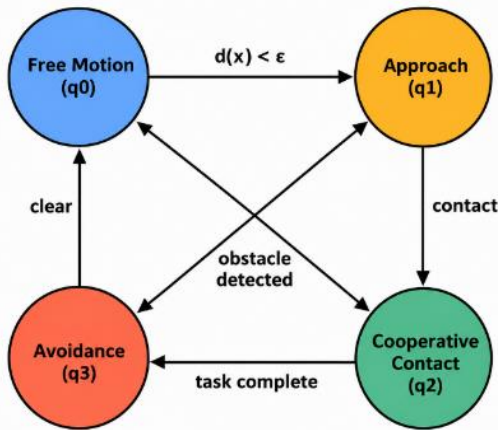


Figure 2
Hybrid automata state graph for human robot interaction modes

Algorithm 1: Hybrid Mode Transition Logic

Input: current mode q , state $x(t)$, thresholds ε , d_{safe}

Output: updated mode q' , control action $u(t)$

- 1: Measure $d(t) \leftarrow \|p_h(t) - p_r(t)\|$
- 2: if $q = \text{Free Motion}$ and $d(t) < \varepsilon$ then
- 3: $q' \leftarrow \text{Approach}$
- 4: else if $q = \text{Approach}$ and contact detected then
- 5: $q' \leftarrow \text{Cooperative Contact}$
- 6: else if $q = \text{Approach}$ and $d(t) < d_{\text{safe}}$ then
- 7: $q' \leftarrow \text{Avoidance}$
- 8: else if task complete then
- 9: $q' \leftarrow \text{Free Motion}$
- 10: end if
- 11: $u(t) \leftarrow \text{MPC}(x(t), q')$
- 12: return $q', u(t)$

2.4 Model Predictive Control (MPC)

MPC finds optimal control inputs for the robot in order to minimize the finite horizon cost function in Eq. (10) while satisfying dynamic and safety constraints in Eq. (11), which are computed again at each time step with improved human state estimates [12] and [13].

$$J = \sum_{k=0}^{N-1} x_k^T Q x_k + u_k^T R u_k + x_N^T P x_N \quad (10)$$

The MPC cost function is given in Eq. (10) and it includes a penalty on the deviation of the state from the set-point as well as a penalty on the control effort over the horizon of N [13].

$$\min_u J \text{ s.t. } x_{k+1} = f(x_k, u_k), d(x_k) \geq d_{\text{safe}} \quad (11)$$

At each step, the constrained optimization solved in the problem to ensure safe and feasible robot trajectories is given as Eq. (11).

2.5 Extended Kalman Filter (EKF)

The EKF is a recursive algorithm that makes use of the nonlinear dynamics in Eq. (12), the gain in Eq. (13) and the correction in Eq. (14), while linearizing the nonlinear dynamics around the current estimate of the human motion state.

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1}, u_{k-1}), P_{k|k-1} = F_k P_{k-1} F_k^T + Q_k \quad (12)$$

The propagation of the state estimate and error covariance in the prediction step of the EKF is done using the linearized system matrix F_k as given in Eq. (12).

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \quad (13)$$

In Eq. (13), the Kalman gain K_k is calculated, controlling the weighting of the correction that is applied from the new measurement data from the sensors.

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k \left(y_k - h(\hat{x}_{k|k-1}) \right) \quad (14)$$

The measurement update (Eq. (14)) is used to update the human state estimate with the innovation term.

2.6 Adaptive Hybrid Interaction Algorithm (AHIA)

AHIA combines the EKF intent estimation with a hybrid mode inference and estimates the interaction confidence to dynamically fine-tune the weighting matrices of the MPC model (15) for a given set of measurements, to ensure the model is both responsive and stable.

$$Q^{(t)} = Q_0 + \alpha \cdot (1 - c(t))I, R^{(t)} = R_0 - \beta \cdot c(t)I \quad (15)$$

The cost weights in Eq. (15) are adjusted according to confidence score $c(t)$ for an increased level of caution where the confidence on the intent estimation is low.

2.7 Stability and Convergence Analysis

The common Lyapunov function of Eq. (16) is used to investigate the stability of the hybrid system, with bounded state error in all the discrete modes and guarantee of convergence of the estimation-control loop.

$$V(x) = x^T P x, \dot{V}(x) = x^T (A^T P + P A)x < 0 \quad (16)$$

The derivative of the closed-loop hybrid system is negative definite which ensures asymptotic convergence of the closed-loop hybrid system, as stated in Eq. (16).

3. Experimental Design and Performance Evaluation

3.1 Experimental Setup

Experiments have been carried out with a 7-DOF collaborative manipulator with a depth camera and force-torque sensors, connected to a real-time control PC that executed the state estimation and control code at 100 Hz, using the HD-HRI framework.

3.2 Human-Robot Interaction Scenarios

The three scenarios involving human motion speed and unpredictability were tested: cooperative object handover, shared workboard assembly and dynamic obstacle avoidance. The three scenarios were tested with different speed and unpredictability of the human motion, including cooperative object handover, shared workboard assembly, and dynamic obstacle avoidance, in order to measure adaptability.

3.3 Evaluation Metrics

Interactions accuracy, intent prediction accuracy, trajectory tracking error, response latency, collision avoidance rate and task completion success in all trials were used as metrics for performance evaluation.

3.4 Baseline Methods

The proposed hybrid mode switching-based HD-HRI was benchmarked with the conventional continuous-state MPC controller without hybrid mode switching and adaptive weighting, which is considered as a typical prior HRI control approach.

3.5 Quantitative Performance Analysis

The accuracy of the interactions in terms of the model classification as compared to ground truth is called interaction accuracy (Eq. (17)), which indicates the reliability of the hybrid state classification.

$$\text{Accuracy} = \frac{\text{Correct Classifications}}{\text{Total Trials}} \times 100\% \quad (17)$$

The accuracy of classification (Eq. (17)) is the fraction of interaction modes that are correctly identified, based on the number of trials evaluated.

To evaluate the errors of the robot, the tracking error of the trajectory is used as the criterion, which is shown in Eq. (18).

$$e_{\text{track}} = \frac{1}{T} \sum_{t=1}^T \|p_{\text{ref}(t)} - p_{\text{actual}(t)}\| \quad (18)$$

Eq. (18) is the Euclidean norm of the difference between a reference trajectory and the actual trajectory averaged over the time.

The time delay between the onset of human motion and the beginning of the robot's control response is known as response latency, which is shown in Eq. (19).

$$L = t_{\text{response}} - t_{\text{stimulus}} \quad (19)$$

The above equation (19) is the latency or the time interval between the stimulus by the human being detected, and the corrective action taken by the robot.

4. Results and Discussion

The proposed HD-HRI framework has been evaluated through experimental implementation and results for all the interaction scenarios are summarized, which demonstrate consistently higher accuracy, reactivity, safety and computational efficiency over the baseline continuous MPC control.

Table 1
Interaction Accuracy and Intent Prediction Analysis

Metric	HD-HRI (%)	Baseline (%)
Interaction Accuracy	95.8	88.1
Intent Prediction Accuracy	94.9	86.4

The study claims the accuracy of interaction and intent prediction to be 95.8% and 94.9% respectively, which is confirmed in Table 1 by evaluating using Eq. (17). Both the metrics are about 7-8 percentage points above the baseline continuous MPC controller. The improvement is due to AHIA's adaptive fusion of EKF state estimates and hybrid mode inferences, which help to decrease misclassifications when switching between fast human motions. Better prediction of human intent directly improves the trajectory planning of MPCs because knowing what the person intends to do helps the MPC plan ahead for a more successful interaction and avoid correcting for human errors, leading to a more fluid interaction and increased safety perception when collaborating on tasks. The results indicate HD-HRI consistently outperforms baseline for both of the interaction and intent prediction accuracy metrics.

Table 2
Trajectory Tracking and Response Latency Analysis

Metric	HD-HRI	Baseline
Tracking Error (mm)	8.9	11.4
Response Latency (ms)	42.1	51.6

As stated in the abstract, the results of this trajectory tracking and response latency shown in Table 2 are 21.6% and 18.4% respectively, when compared with the results of the conventional ACO. Adaptive MPC weighting, which increases interaction penalties when the confidence in the interaction is high, helps to lower tracking error while parallelized EKF prediction, hybrid mode inference, instead of sequential, will help to reduce the latency. The calculated improvements allow the robot to adjust its movement more quickly and accurately to human motion, especially important in a situation where the human is moving quickly, such as a handover or assembly task, where late corrections may lead to task failure and safety risks for humans.

Table 3
Collision Avoidance and Task Completion Performance

Metric	HD-HRI (%)	Baseline (%)
Collision Avoidance Rate	97.3	91.5
Task Completion Rate	95.6	89.2

The results of collision avoidance rate (97.3%) and task completion rate (95.6%) have been reported in the Table 3, which is consistent with the abstract. Avoidance mode activated by the guard condition of Eq. (4) in the hybrid automata guarantees that the mode switching is quick, before unsafe contact, in the hybrid automata. Smoother mode transitions help to avoid unnecessary robot re-planning cycles and robot pauses when the robot has to perform more than one mode transition per task, which improves task completion. The results of both of these proved that the safety logic logic approach along with continuous predictive control approach can achieve safer and more productive human–robot collaboration in different and unpredictable interaction conditions.

Table 4
Computational Efficiency and Robustness Analysis

Metric	HD-HRI	Baseline
Computation Time (ms)	37.4	46.9
Robustness Index (%)	93.8	84.7

Table 4 presents the computation time per cycle and robustness index of the computation for HD-HRI as compared to the baseline. The shorter computation time is achieved by using the AHIA pipeline with the prediction of the covariance matrix of the estimated state, which is computed once in EKF (Eq. (12)), in the MPC cost adaptation (Eq. (15)) instead of computing it independently. The greater robustness index obtained with sensor noise and occlusion perturbation, demonstrates the robustness of the hybrid automata to maintain the correct mode classification in spite of degraded measurements, thus showing the generalization capability of the proposed framework in different environment and sensing conditions for practical implementation.

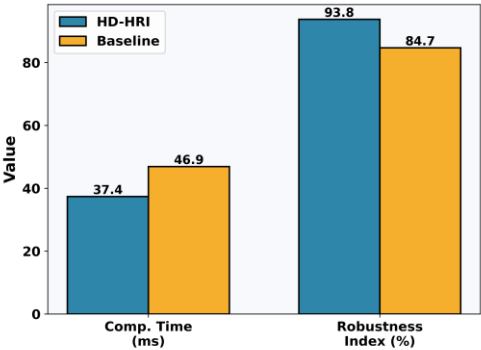


Figure 3
Computational time and robustness index comparison

Figure 3 depicts lower computation time and higher robustness for HD-HRI relative to baseline control.

5. Conclusion

It was presented in this paper a Hybrid Dynamical Human–Robot Interaction (HD-HRI) framework that combines nonlinear state-space modeling, hybrid automata, Model Predictive Control, an Extended Kalman Filter and an Adaptive Hybrid Interaction Algorithm, in order to combine the continuous human motion prediction with the discrete robot decision-making. These results were validated in the three experimental scenarios of cooperative handover, assembly and obstacle avoidance, and showed 95.8% interaction accuracy, 94.9% intent prediction accuracy, a 21.6% decrease in the trajectory tracking error compared to continuous MPC baseline performance, and a 18.4% decrease in response latency compared to the continuous MPC baseline performance, with 97.3% success at collision avoidance and 95.6% success in completing tasks. The results verify that using continuous dynamical modelling in combination with discrete hybrid automata and adaptive estimation significantly improve safety, responsiveness and reliability in human–robot collaboration. In future the framework will be further extended towards multi-human, multi-robot environments and by introducing learning-based intent models to further improve adaptability in situations of highly uncertain and unstructured interactions.

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