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Bayesian Optimization-based Modular Indirect Adaptive Control for a Class of Nonlinear Systems Bayesian Optimization-based Modular Bayesian Optimization-based Modular Bayesian Optimization-based Modular Bayesian Optimization-based Modular Indirect Adaptive Control for a Class of Indirect Adaptive Control for a Class of Nonlinear Systems Nonlinear Systems

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∗∗ *Amir-massoud Farahmand (farahmand@merl.com) is with MERL.* crass of hominear systems with parametric uncertainties. We propose to use a *modular adaptive* approach, where we first design a robust nonlinear state feedback which renders the closed approach, where we first design a robust hominear state recuback which relides the closed
loop input-to-state stable (ISS). The input is considered to be the estimation error of the loop input-to-state stable (i.s.). The input is considered to be the estimation error of the
uncertain parameters, and the state is considered to be the closed-loop output tracking error. We augment this robust ISS controller with a model-free learning algorithm to estimate the we augment this robust is controller with a model-free learning algorithm to estimate the
model uncertainties. We implement this method with a Bayesian optimization-based method moder uncertainties. We implement this method with a Bayesian optimization-based method
called Gaussian Process Upper Confidence Bound (GP-UCB). The combination of the ISS called Gaussian 1 locess opper Communic Bound (GI-0CB). The combination of the 1555
feedback and the learning algorithms gives a *learning-based modular indirect adaptive controller*. becausal and the learning algorithms gives a *tearning-based modular marrier diasphoe controller*.
We test the efficiency of this approach on a two-link robot manipulator example, under noisy measurements conditions. Abstract: We study in this paper the problem of adaptive trajectory tracking control for a class of nonlinear systems with parametric uncertainties. We propose to use a modular adaptive
class of nonlinear systems with parametric uncertainties. We propose to use a modular adaptive
cancerate which when the algorit recuback and the learning algorithms gives a *tearning-oased modular matricet diaspine controller*.
We test the efficiency of this approach on a two-link robot manipulator example, under noisy We test the efficiency of this approach on a two-link robot manipulator example, under noisy measurements conditions. feedback and the learning-based modular individual modular individual and the effect addaptive conditions. We test the effect of this approach on a two-link robot manipulator example, under noisy of the effect of the effec

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1. INTRODUCTION 1. INTRODUCTION 1. INTRODUCTION 1. INTRODUCTION

measurements conditions.

Many adaptive methods have been proposed over the years for linear and nonlinear systems, e.g., Krstic et al. [1995]. In this work we focus on a specific type of adaptive control, namely, the indirect modular approach to adaptive nonlinear control, e.g., Krstic et al. [1995], Wang et al. [2006], Benosman and Atinc [2013], Atinc and Benosman [2013], Benosman [2014b,a], Xia and Benosman [2015], Lavretsky Benosman [20140,a], Ala and Benosman [2015], Lavretsky
[2009], Haghi and Ariyur [2011]. In the direct approach, (2009), Hagin and Arry at [2011]. In the direct approach,
first a controller is designed by assuming that all the parameters are known (certainly equivalence principle), parameters are known (certainly equivalence principle),
and then an identifier is used to estimate the unknown and then an identifier is used to estimate the unknown
parameters online. The identifier might be independent parameters omine. The identifier inight be independent
of the designed controller, in which case the approach of the designed controller, in which case the approach
is called 'modular'. A modular approach has been prois called modular. A modular approach has been pro-
posed in Wang et al. [2006] for adaptive neural control posed in wang et al. [2000] for adaptive neural control
of pure-feedback nonlinear systems, where the input-toor pure-recuback hominear systems, where the input-to-
state stability (ISS) modularity of the controller-estimator state stability (i.s.) inodularity of the controller-estimator
is achieved and the closed-loop stability is guaranteed by the small-gain theorem, e.g., Sontag [1989]. Many adaptive methods have been proposed over the years B mamely, the indirect modular approach to adaptive nonlinear control, e.g., Krstic et al. [1995], Wang et al. [2006], Benosman and Atinc [2013], Atinc and Benosman [2013], namely, the indirect modular approach to adaptive nonlinear control, e.g., Krstic et al. [1995], Wang et al. [2006], Benosman and Atinc [2013], Atinc and Benosman [2013], Many adaptive methods have been proposed over the years
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namely the indiced modular approach to adaptive poplin namely, the indirect modular approach to adaptive nomin-
ear control .e.c. Kratie et al. [1005]. Wang et al. [2006]. ear control, e.g., Krstic et al. [1995], Wang et al. [2000],
Denomen end Ating [9019] Ating and Denomen [9019] Benosman and Atinc [2013], Atinc and Benosman [2013], is achieved and the closed-loop stability is guaranteed by
the small sain theorem e.g. Sontage [1090]

In this work, we present a modular adaptive design which In this work, we present a modular adaptive design which
combines model-free learning methods and robust modelcombines model-the learning methods and robust model-
based nonlinear control to propose a learning-based modubased nonlinear control to propose a learning-based modular indirect adaptive controller. Here, a model-free learning algorithm is used to estimate in closed-loop the uncertain
algorithm is used to estimate in closed-loop the uncertain algorithm is used to estimate in closed-loop the uncertain
parameters of the model. The main difference with the parameters of the model. The main unterence with the
existing model-based indirect adaptive control methods, is the fact that we do not use the model to design the paramethe fact that we do not use the model to design the parame-
ters estimation filters. Indeed, model-based indirect adaptive controllers are based on parameters' estimators designed using the model of the system, e.g., the X-swapping signed using the model of the system, e.g., the X-swapping
methods presented in Krstic et al. [1995]. Here, because we do not use the system dynamics to design the estimation filters we can deal with a more general class of uncertainliners we can dear with a more general class of uncertain-
ties, e.g., nonlinear uncertainties can be estimated with the proposed approach, see Atinc and Benosman [2013] for the proposed approach, see Atinc and Benosman [2013] for ties, e.g., nonlinear uncertainties can be estimated with In this work, we present a modular adaptive design which f methods presented in Krstic et al. $[1995]$. Here, because we signed using the model of the system, e.g., the X-swapping signed using the model of the system, e.g., the X-swapping
methods presented in Krstic et al. [1995]. Here, because we In this work, we present a modular adaptive design which methods presented in Krstic et al. $[1995]$. Here, because we signed using the model of the system, e.g., the X-swapping methods presented in Krstic et al. [1995]. Here, because we existing model-based indirect adaptive control methods, is ters estimation filters. Indeed, model-based indirect adaptive controllers are based on parameters' estimators designed using the model of the system, e.g., the A-swapping
mothods presented in Krstie et al. [1005]. Here, because we methods presented in Krstic et al. [1995]. Here, because we the proposed approach, see Atinc and Benosman [2013] for some preliminary results. Furthermore, with the proposed some premimiary results. Furthermore, with the proposed
approach we can estimate a vector of linearly dependent approach we can estimate a vector of mearly dependent
uncertainties, a case which cannot be solved using modeldifferent different called the solved using model-
based filters, e.g., in Benosman and Atinc [2015] it is shown based inters, e.g., in Benosman and Atinc [2015] It is shown
that the X-swapping model-based method fails to estimate a vector of linearly dependent parameters. some preliminary results. Furthermore, with the proposed some preliminary results. Furthermore, with the proposed that the x-swapping model-based method fails to estimate
a vector of linearly dependent parameters

In this work, we implement the proposed approach with in this work, we implement the proposed approach with
a Bayesian optimization-based method called GP-UCB. The latter solves the exploration-exploitation problem in The latter solves the exploration-exploration problem in
the continuous armed bandit problem, which is a nonassociative reinforcement learning (RL) setting. In this work, we implement the proposed approach with \overline{P} In this work, we implement the proposed approach with $\sum_{i=1}^{n}$ a Bayesian optimization-based method called GP-UCB.
The letter selves the evolution evolutation problem in the continuous armed bandit problem, which is a non-

We want to underline here that compared to 'pure' modelwe want to underline here that compared to pure mode-
free controllers, e.g., pure RL algorithms, the proposed control has a different goal. The available model-free concontrol has a unterent goal. The available model-nee con-
trollers are meant for output or state regulation. In the contrary, here we propose to use model-free learning to complement a model-based nonlinear control to estimate the unknown parameters of the model. Here the control the unknown parameters of the model. Here the control
goal, i.e., state or output trajectory tracking, is handled by goal, i.e., state of output trajectory tracking, is nanded by
the model-based controller. The learning algorithm is used to improve the tracking performance of the model-based to improve the tracking performance of the model-based
controller. Once the learning algorithm has converged, one controller. Once the learning algorithm has converged, one
can carry on using the nonlinear model-based feedback controller alone, without the need of the learning algocontroller alone, while the need of the learning algorithm. Moreover, we believe that this type of controller can The Euclidean Converge faster to an optimal performance, comparatively converge aster to an optimal performance, comparatively
to the pure model-free controller. The reason is that the to the pute model-free controller. The reason is that the
model-free algorithms assume no knowledge about the model-ifee algorithms assume no knowledge about the
system, and thus start the search for an optimal control signal from scratch. On the other hand, by 'partly' using a model-based controller we are taking advantage of the a model-based controller we are taking advantage of the partial information given by the physics of the system. We want to underline here that compared to 'pure' model-We want to underline here that compared to 'pure' modelfree controllers, e.g., pure RL algorithms, the proposed
control has a different goal. The available model free can contrary, here we propose to use model-free learning to
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controller alone, without the need of the learning algo system, and thus start the search for an optimal control partial information given by the physics of the system.

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Benosman [2013], Benosman [2014b.a], Xia and Benosman Benosman [2013], Benosman [2014b,a], Xia and Benosman Benosman [2013], Benosman [2014b,a], Xia and Benosman A modular design merging model-based control and an A modular design merging model-based control and an extremum seeker has been proposed in Haghi and Ariyur

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[2015]. In Haghi and Ariyur [2011, 2013], extremum seeking is used to complement a model-based controller, under linearity of the model assumption in Haghi and Ariyur [2011], or under the assumption of linear parametrization of the control in terms of the uncertainties in Haghi and Ariyur [2013]. The modular design idea of using a modelbased controller with ISS guarantee, complemented with an ES-based module can be found in Atinc and Benosman [2013], Benosman [2014b,a], Xia and Benosman [2015], where the ES was used to estimate the model parameters, and in Benosman and Atinc [2013], Benosman [2015] where feedback gains were tuned using ES algorithms. The work of this paper falls in this class of ISS-based modular indirect adaptive controllers. The difference with other ES-based adaptive controllers is that, due to the ISS modular design we can use any model-free learning algorithm to estimate the model uncertainties, not necessarily extremum seeking-based. To emphasize this we show here the performance of the controller when using a type of RL-based learning algorithm.

The rest of the paper is organized as follows. In Section 2, we formulate the problem. The nominal controller design are presented in Section 3. In Section 3.2, a robust controller is designed which guarantees ISS from the estimation error input to the tracking error state. In section 3.3, we introduce the RL GP-UCB algorithm as a modelfree learning to complement the ISS controller. Section 4 is dedicated to an application example and the paper conclusion is given in Section 5.

Throughout the paper, we use $\|\cdot\|$ to denote the Euclidean norm; i.e., for a vector $x \in \mathbb{R}^n$, we have $||x|| \triangleq$ $||x||_2 = \sqrt{x^T x}$, where x^T denotes the transpose of the vector x. We denote by $Card(S)$ the size of a finite set S. The Frobenius norm of a matrix $A \in \mathbb{R}^{m \times n}$, with elements a_{ij} , is defined as $||A||_F \triangleq \sqrt{\sum_{i=1}^n \sum_{j=1}^n |a_{ij}|^2}$. Given $x \in \mathbb{R}^m$, the signum function is defined as $sign(x) \triangleq [sign(x_1), sign(x_2), \cdots, sign(x_m)]^T$, where sign(.) denotes the classical signum function.

2. PROBLEM FORMULATION

We consider here affine uncertain nonlinear systems of the form

$$
\begin{array}{rcl}\n\dot{x} & = & f(x) + \Delta f(t, x) + g(x)u, \\
y & = & h(x),\n\end{array} \tag{1}
$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^p$, $y \in \mathbb{R}^m$ $(p \geq m)$, represent the state, the input and the controlled output vectors, respectively. $\Delta f(\bar{t}, x)$ is a vector field representing additive model uncertainties. The vector fields f, Δf , columns of g and function h satisfy the following assumptions.

Assumption A1 The function $f : \mathbb{R}^n \to \mathbb{R}^n$ and the columns of $g : \mathbb{R}^n \to \mathbb{R}^p$ are \mathbb{C}^∞ vector fields on a bounded set X of \mathbb{R}^n and $h : \mathbb{R}^n \to \mathbb{R}^m$ is a \mathbb{C}^∞ vector on X. The vector field $\Delta f(x)$ is \mathbb{C}^1 on X.

Assumption A2 System (1) has a well-defined (vector) relative degree $\{r_1, r_2, \cdots, r_m\}$ at each point $x^0 \in X$, and the system is linearizable, i.e., $\sum_{i=1}^{m} r_i = n$.

Assumption A3 The desired output trajectories y_{id} $(1 \leq i \leq m)$ are C^{∞} functions of time, relating desired initial points $y_{id}(0)$ at $t = 0$ to desired final points $y_{id}(t_f)$ at $t = t_f$.

Our objective is to design a state feedback adaptive controller such that the output tracking error is uniformly

bounded, whereas the tracking error upper-bound is function of the uncertain parameters estimation error, which can be decreased by the model-free learning. We stress here that the goal of learning algorithm is not stabilization but rather performance optimization, i.e., the learning improves the parameters' estimation error, which in turn improves the output tracking error. To achieve this control objective, we proceed as follows: First, we design a robust controller which can guarantee input-to-state stability (ISS) of the tracking error dynamics w.r.t the estimation errors input. Then, we combine this controller with a model-free learning algorithm to iteratively estimate the uncertain parameters, by optimizing online a desired learning cost function.

3. ADAPTIVE CONTROLLER DESIGN

3.1 Nominal Controller

Let us first consider the system under nominal conditions, i.e., when $\Delta f(t, x) = 0$. In this case, it is well know, e.g., Khalil [2002], that system (1) can be written as

$$
y^{(r)}(t) = b(\xi(t)) + A(\xi(t))u(t), \tag{2}
$$

where

$$
y^{(r)}(t) = [y_1^{(r_1)}(t), y_2^{(r_2)}(t), \cdots, y_m^{(r_m)}(t)]^T,
$$

\n
$$
\xi(t) = [\xi^1(t), \cdots, \xi^m(t)]^T,
$$

\n
$$
\xi^i(t) = [y_i(t), \cdots, y_i^{(r_i-1)}(t)], \quad 1 \le i \le m
$$
\n(3)

The functions $b(\xi)$, $A(\xi)$ can be written as functions of f, g and h, and $A(\xi)$ is non-singular in \tilde{X} , where \tilde{X} is the image of the set of X by the diffeomorphism $x \to \xi$ between the states of system (1) and the linearized model (2). Now, to deal with the uncertain model, we first need to introduce one more assumption on system (1).

Assumption A4 The additive uncertainties $\Delta f(t, x)$ in (1) appear as additive uncertainties in the input-output linearized model (2)-(3) as follows:

$$
y^{(r)}(t) = b(\xi(t)) + A(\xi(t))u(t) + \Delta b(t, \xi(t)), \quad (4)
$$

where $\Delta b(t,\xi)$ is \mathbb{C}^1 w.r.t. the state vector $\xi \in X$.

It is well known that the nominal model (2) can be easily transformed into a linear input-output mapping. Indeed, we can first define a virtual input vector $v(t)$ as

$$
v(t) = b(\xi(t)) + A(\xi(t))u(t).
$$
 (5)

Combining (2) and (5), we can obtain the following inputoutput mapping

$$
y^{(r)}(t) = v(t). \tag{6}
$$

Based on the linear system (6), it is straightforward to design a stabilizing controller for the nominal system (2) as

$$
u_n = A^{-1}(\xi) [v_s(t, \xi) - b(\xi)],
$$
\n(7)

where v_s is a $m \times 1$ vector and the *i*-th $(1 \le i \le m)$ element v_{si} is given by

$$
v_{si} = y_{id}^{(r_i)} - K_{r_i}^i (y_i^{(r_i - 1)} - y_{id}^{(r_i - 1)}) - \dots - K_1^i (y_i - y_{id}).
$$
\n(8)

If we denote the tracking error as $e_i(t) \triangleq y_i(t) - y_{id}(t)$, we obtain the following tracking error dynamics

$$
e_i^{(r_i)}(t) + K_{r_i}^i e^{(r_i - 1)}(t) + \dots + K_1^i e_i(t) = 0,
$$
 (9)

where $i \in \{1, 2, \cdots, m\}$. By properly selecting the gains K_j^i where $i \in \{1, 2, \cdots, m\}$ and $j \in \{1, 2, \cdots, r_i\}$, we can obtain global asymptotic stability of the tracking errors $e_i(t)$. To formalize this condition, we add the following assumption.

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