The adaptive schemes proposed in this paper advance the state-of-the-art of adaptive nonlinear output-feedback control in several directions. They remove the main drawbacks of the original Marino–Tomei design. Only the minimal number of parameters is updated, and any standard update law can be incorporated in the swapping-based scheme. The estimation-based approach can now be used for adaptive nonlinear output-feedback control without any growth restrictions. The modifications made in the Marino–Tomei controller make it possible to systematically improve the transient performance by increasing certain design parameters.

VIII. CONCLUSIONS

The adaptive schemes proposed in this paper advance the state-of-the-art of adaptive nonlinear output-feedback control in several directions. They remove the main drawbacks of the original Marino–Tomei design. Only the minimal number of parameters is updated, and any standard update law can be incorporated in the swapping-based scheme. The estimation-based approach can now be used for adaptive nonlinear output-feedback control without any growth restrictions. The modifications made in the Marino–Tomei controller make it possible to systematically improve the transient performance by increasing certain design parameters.

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Adaptive Control of a Class of Decentralized Nonlinear Systems

Jeffrey T. Spooner and Kevin M. Passino

Abstract—Within this brief paper, a stable indirect adaptive controller is presented for a class of interconnected nonlinear systems. The feedback and adaptation mechanisms for each subsystem depend only upon local measurements to provide asymptotic tracking of a reference trajectory. In addition, each subsystem is able to adaptively compensate for disturbances and interconnections with unknown bounds. The adaptive scheme is illustrated through the longitudinal control of a string of vehicles within an automated highway system (AHS).

I. INTRODUCTION

Decentralized control systems often arise from either the physical inability for subsystem information exchange or the lack of computing capabilities required for a single central controller. Furthermore, difficulty and uncertainty in measuring parameter values within a large-scale system may call for adaptive techniques. Since these restrictions encompass a large group of applications, a variety of decentralized adaptive techniques have been developed. Model reference adaptive control (MRAC)-based designs for decentralized systems have been studied in [1]–[4] for the continuous time case and in [5] and [6] for the discrete time case. These approaches, however, are limited to decentralized systems with linear subsystems and possibly nonlinear interconnections. Decentralized adaptive controllers for robotic manipulators were presented in [7]–[9], while a scheme for nonlinear subsystems with a special class of interconnections was presented in [10].

Our objective is to present adaptive controllers for a class of decentralized systems with nonlinear subsystems, unknown nonlinear interconnections, and disturbances with unknown bounds. This paper is organized as follows: In Section II, the details of the problem statement for the decentralized system are presented. The adaptive algorithms for each subsystem using only local information are presented, and composite system stability is established in Section III. An illustrative example is then used in Section IV to demonstrate the effectiveness of the decentralized adaptive technique.

II. PROBLEM STATEMENT

Our objective is to design an adaptive control system for each subsystem which will cause the output, $y_{mi}$, of a relative degree $r_i$ subsystem, $S_i$, to track a desired output trajectory, $y_{m_i}$, in the presence of interconnections, $I_{ij}$, and unknown disturbances using only local measurements (see Fig. 1). The desired output trajectory, $y_{m_i}$, may be defined by a signal external to the control system so that the first $r_i$ derivatives of the $i$th subsystem’s reference signal $y_{m_i}$ may be measured by a reference model with relative degree greater than or equal to $r_i$ which characterizes the desired performance. It is thus assumed that the desired output trajectory and its derivatives $y_{m_1}, \ldots, y_{m_{r_i}}$ for the $i$th subsystem, $S_i$, are measurable and bounded (let $y_{m_i}$ denote the $r_i$th derivative of $y_{m_i}$ with respect to time). Within this paper an "output error indirect adaptive controller" is
Throughout the analysis to follow, both are exponentially attractive \([12]\).

It is also assumed that the zero dynamics for each subsystem nonlinear dynamics of the subsystem that have unknown parameters. The following analysis may easily be modified for subsystems which are defined with

\[
\dot{y}_i = f_i(t, X_i, \ldots, X_m) + g_i(X_i)u_{pi}
\]

where \(X_i \in \mathbb{R}^n\) is the state vector, \(u_{pi} \in \mathbb{R}\) is the input, and \(y_{pi} \in \mathbb{R}\) is the output of the plant for the \(i\)th subsystem, \(S_i\), and the functions \(f_i(t, X_i, \ldots, X_m)\) and \(g_i(X_i)\) are smooth. If each subsystem has "strong relative degree" \(r_i\), then

\[
X_i = f_i(t, X_i, \ldots, X_m) + g_i(X_i)u_{pi}
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where \(X_i \in \mathbb{R}^n\) is the state vector, \(u_{pi} \in \mathbb{R}\) is the input, and \(y_{pi} \in \mathbb{R}\) is the output of the plant for the \(i\)th subsystem, \(S_i\), and the functions \(f_i(t, X_i, \ldots, X_m)\) and \(g_i(X_i)\) are smooth. If each subsystem has "strong relative degree" \(r_i\), then

\[
\dot{y}_i = f_i(t, X_i, \ldots, X_m) + g_i(X_i)u_{pi}
\]

where \(L_{g_i} h_i(t, X_i, \ldots, X_m)\) is the Lie derivative of \(h_i(t, X_i, \ldots, X_m)\) with respect to \(g_i(L_{g_i} h_i(t, X_i, \ldots, X_m)) = \frac{\partial}{\partial x_i} g_i(X_i)\), e.g., \(L_{g_i} h_i(t, X_i, \ldots, X_m) = L_{g_i} h_i(t, X_i, \ldots, X_m)\), and it is assumed that for some \(\beta_i > 0\), we have \([\beta_i(t) + \beta_i(X_i)] \geq \beta_i\), so that it is bounded away from zero (for convenience we assume that \(\Delta_i(t) + \beta_i(X_i) > 0\); however, the following analysis may easily be modified for subsystems which are defined with \(\beta_i(t) + \beta_i(X_i) < 0\). The effects of the interconnections, \(I_{ij}\), upon the subsystem \(S_i\) are accounted for within the term \(\Delta_i(t, X_i, \ldots, X_m)\). We will assume that \(\alpha_i(t)\) and \(\beta_i(t)\) are known components of the dynamics of the \(i\)th subsystem, \(S_i\), or time dependent signals, and that \(\alpha_i(X_i)\) and \(\beta_i(X_i)\) represent nonlinear dynamics of the subsystem that have unknown parameters. Throughout the analysis to follow, both \(\alpha_i(t)\) and \(\beta_i(t)\) may be set to zero. It is also assumed that the zero dynamics for each subsystem are exponentially attractive \([12]\).
and \( b_i = [0 \ 0 \ \cdots \ 0 \ 1]^T \in \mathbb{R}^n \). It is assumed that the interconnections satisfy

\[
\Delta_i(t, X_1, \cdots, X_m) = d_i(t) + \delta_i(t, X_1, \cdots, X_m) \tag{12}
\]

where \( |d_i(t, X_1, \cdots, X_m)| \leq \sum_{j=1}^m \gamma_{i,j} |e_j(t)| \) is the Euclidean vector norm. The scalars \( \gamma_{i,j} \) quantify the strength of the interconnections. Let \( c_i^* = (\sup |d_i(t)| - \inf |d_i(t)|)/2 \) be a measure of the variation of \( d_i(t) \) and \( d_i = (\exp |d_i(t)| + \inf |d_i(t)|)/2 \) is a measure of the center of position of \( d_i(t) \). We may thus let \( d_i(t) = d_i + \delta_i(t) \), where \( |\delta_i| \leq c_i^* \), with \( c_i^* \) assumed to be bounded. Also, if \( d_i \) is nonzero, we may absorb \( d_i \) into \( \alpha_i(X_i) \) within (4) as an unknown constant. Within the adaptation algorithm, the bound \( c_i \) will be estimated by \( e_i \), with the corresponding parameter error defined as \( \phi_i := c_i - c_i^* \). Also define \( H_i^* = [\gamma_1^*, \cdots, \gamma_m^*] \) as a vector of desired gains which shall be defined later. Each \( \gamma_i \) will adapt to achieve these feedback gains with a parameter error \( \phi_{i} = \gamma_{i} - \gamma_{i}^* \).

Consider the following Lyapunov function type for the \( i \)-th subsystem

\[
v_i = \frac{e_i^T}{2} P_i e_i + \frac{1}{2} \sum_{j=1}^m \gamma_{i,j} \sum_{l=1}^m q_{ij} \phi_{jl} + \frac{1}{2} \sum_{j=1}^m \gamma_{i,j} \sum_{l=1}^m q_{ij} \phi_{jl} + q_{ij} \phi_{ij} + q_{ij} \phi_{ij} \tag{13}
\]

where each \( P_i \in \mathbb{R}^{n 	imes n}, q_{ij} \in \mathbb{R}^{n}, q_{ij} \in \mathbb{R}^{n}, \) and \( Q_{ij} \in \mathbb{R}^{n} \) are some positive definite and symmetric matrices with each \( q_{ij}, q_{ij} > 0 \) a constant. Taking the time derivative yields

\[
v_i = \frac{e_i^T}{2} P_i e_i + \frac{1}{2} \sum_{j=1}^m \gamma_{i,j} \sum_{l=1}^m q_{ij} \phi_{jl} + 2q_{ij} \phi_{ij} + \frac{1}{2} \sum_{j=1}^m \gamma_{i,j} \sum_{l=1}^m q_{ij} \phi_{jl} + q_{ij} \phi_{ij} + q_{ij} \phi_{ij} \tag{14}
\]

Since each \( \gamma_i \) is positive definite, given some positive definite \( R_i \), there exists a unique symmetric positive definite \( P_i \) satisfying

\[
\dot{A}_{ri} = -Q_{ri}^{-1} C_r e_i^T P_i b \tag{15}
\]

\[
\dot{B}_{ri} = -Q_{ri}^{-1} C_r e_i^T P_i b u_i \tag{16}
\]

\[
\dot{c}_i = \frac{1}{q_{i}} e_i^T P_i b \tag{17}
\]

\[
\dot{\eta}_i = \frac{1}{2q_{i}} (e_i^T P_i b)^2. \tag{18}
\]

The update laws, (15) and (16), are used to estimate the dynamics of the subsystem under control, while (17) and (18) are used to stabilize the subsystems by estimating the effects of the interconnections. Both (17) and (18) increase monotonically, however, so a projection algorithm may be required to ensure that they do not become unnecessarily large. Note that while our update laws (15) and (16) for the subsystems bear some similarity to those in [12], our control laws are different.

The update laws, (15), are used to estimate the dynamics of the subsystem by estimating the effects of the interconnections.
rates may be safely achieved. Since many of today's automobile
follow a lead vehicle at a safe distance (car following, see Fig. 2),
may actually increase the safety of the highway. Vehicles will be
driven automatically with onboard lateral and longitudinal controllers.
comers, make lane changes, and perform additional steering tasks.
accidents are caused by human error, automating the driving process
The longitudinal controllers will be used to maintain a steady
convergence of the tracking errors will no longer be guaranteed.
Due to increasing traffic congestion, there has been an renewed
IV. EXAMPLE: AN AUTOMATED HIGHWAY SYSTEM
Due to increasing traffic congestion, there has been an renewed
interest in the development of an AHS in which high traffic flow
rates may be safely achieved. Since many of today’s automobile
accidents are caused by human error, automating the driving process
may actually increase the safety of the highway. Vehicles will be
driven automatically with onboard lateral and longitudinal controllers.
The lateral controllers will be used to steer the vehicles around
corners, make lane changes, and perform additional steering tasks.
The longitudinal controllers will be used to maintain a steady
velocity if a vehicle is traveling alone (conventional cruise control),
follow a lead vehicle at a safe distance (car following, see Fig. 2),
or perform other speed/tracking tasks. Here we consider the
car-following problem in which only tracking information is available
(as opposed to information about lead and other subsequent vehicles)
to each following vehicle [16]. For more details on intelligent vehicle
highway systems (IVHS), see [17] and [18].
The dynamics of the car-following system for the ith vehicle
may be described by the state vector $X_i = [\psi_i, v_i, f_i]^T$, where
$\psi_i = x_i - x_{i-1}$ is the intervehicle spacing between the ith and $i-1$st
vehicles, $v_i$ is the ith vehicle’s velocity, and $f_i$ is the driving/braking
force applied to the longitudinal dynamics of the ith vehicle. The
longitudinal dynamics may be expressed as
\[ \dot{\psi} = v - v_{i-1} \]
\[ \dot{v} = \frac{1}{m} (-A_p v^2 - d + f) \]
\[ \dot{f} = \frac{1}{\tau} (f + u_p) \]
where $u_p$ is the control input (if $u_p > 0$, then it represents a throttle
input, and if $u_p < 0$, it represents a brake input), and the vehicle
variables and parameters are summarized in Table 1 (we assume that
the variables and parameters are associated with the ith vehicle, unless
subscripts indicate otherwise).
The plant output is $y_p = \psi + L + \rho v, L, \rho > 0$. This measurement
allows for a velocity-dependent intervehicle spacing [19] due to the
$\rho v$ term plus an additional constant intervehicle spacing of $L$. As
the velocity of the ith vehicle increases, the distance between the $i$th
and $i-1$st vehicles should increase. A standard good driving rule for
humans is to allow an intervehicle spacing of one vehicle length per
10 mph (this roughly corresponds to $\rho = 0.9$). With $\rho \neq 0$, the plant
is of relative degree two since
\[ y_p(\cdot) = \frac{1}{m} (-A_p v^2 - d + f) + \frac{\rho}{m} (-2A_p v \dot{\psi} - \frac{1}{\tau} f) \]
\[ + \frac{\rho}{m \tau} u_p - \dot{\psi}_{i-1} \]
This is of the form required by the decentralized adaptive controller
with
\[ \alpha(X) = \frac{1}{m} (-A_p v^2 - d + f) + \frac{\rho}{m} (-2A_p v \dot{\psi} - \frac{1}{\tau} f) \]
\[ \beta(X) = \frac{\rho}{m \tau} \]
Fig. 3. Velocity profiles of a six-car string of vehicles.

Fig. 4. Spacing errors for the five following cars.

where $\Delta = -\hat{v}_{i-1}$. Since we desire that $y_p \to 0$, here we simply select $y_m := 0$ so that

$$e_o = -y_p. \quad (35)$$

Notice that if $v > 0$ and $y_p$ is forced to zero, then $\psi$ will be negative. This implies that $x_{i-1} > x_i$ (i.e., the $i$-th vehicle is ahead of the $(i+1)$-th vehicle). Since $\Delta = \frac{1}{\rho}e_{n-1} - \frac{1}{\rho}(v_{i-1} - v_{i-2}),$ the interconnections may be bounded with $|y_{n-1}| = 1/\rho,$ and $d_i(t) \leq |v_{i-1} - v_{i-2}|/\rho.$ Also $|v_{i-1} - v_{i-2}|$ is bounded for the $i$-th vehicle since if $i = 0$ (corresponding to the lead vehicle), then we may consider $d_i = 0.$ Thus the above adaptive technique may be applied to the first following car, $i = 1$, with bounded tracking so that $|v_4 - v_0|$ is bounded. Thus this technique may be applied to the second following vehicle, and so on.

For this example, we choose $R_s = diag\{1,1\}$ and $L_s(s) = s^2 + 2s + 1.$ With $\lambda_i = 1$ and each $v_i = 1$ (tracking performance for each car is weighted equally), using the arguments for the existence of some $\eta$ large enough for feedback stabilization, we see that $\eta = 1/\rho^2$ is sufficient for diagonal dominance (we shall not adapt $\eta_i$ since a stabilizing gain is known). From (33), we choose $\bar{c}_o = [1; v_y^2, v_y v_i, f_i]$ and $\bar{c}_i = [1].$ The adaptation rates were chosen as $Q_{\bar{c}_o} = diag\{0.01,0.01,0.01,0.01\}, Q_{\bar{c}_i} = [0.01],$ and $\rho_i = [0.1].$ The parameter estimates were initially set to zero, except for $B_{\bar{c}_i}(0) = 0.01.$ In addition, a projection algorithm was used to ensure that $A_{\bar{c}_i} \geq 0.001,$ and the smoothing technique of Remark 4 was used with $c_i = 0.001.$

A string of vehicles with five following vehicles was considered in the simulation analysis with $L = 2$ and $\rho = 0.4.$ The vehicles states were initialized with no intervehicle spacing or velocity errors. The velocity profiles for the string of vehicles is shown in Fig. 3 [plots are labeled with lead vehicle (-----), car #1 (- - -), car #2 (- - -), car #3 (- - -), car #4 (- - -), car #5 ( ---)]. The intervehicle spacing errors are shown in Fig. 4. The adaptive controllers are able to quickly provide good tracking.

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