



Dynamic neural network-based robust observers for uncertain nonlinear systems[☆]

H.T. Dinh^{a,*}, R. Kamalapurkar^b, S. Bhagat^c, W.E. Dixon^b

^a Department of Mechanical Engineering, University of Transport and Communications, Viet Nam

^b Department of Mechanical and Aerospace Engineering, University of Florida, Gainesville, FL 32611-6250, USA

^c Department of Electrical Engineering, Indian Institute of Technology, Delhi, India

ARTICLE INFO

Article history:

Received 12 August 2013

Revised and accepted 19 July 2014

Available online 1 August 2014

Keywords:

Neural networks

Output feedback

Robust adaptive control

Lyapunov method

ABSTRACT

A dynamic neural network (DNN) based robust observer for uncertain nonlinear systems is developed. The observer structure consists of a DNN to estimate the system dynamics on-line, a dynamic filter to estimate the unmeasurable state and a sliding mode feedback term to account for modeling errors and exogenous disturbances. The observed states are proven to asymptotically converge to the system states of high-order uncertain nonlinear systems through Lyapunov-based analysis. Simulations and experiments on a two-link robot manipulator are performed to show the effectiveness of the proposed method in comparison to several other state estimation methods.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

Full state feedback is not available in many practical systems. In the absence of sensors, the requirement of full-state feedback for the controller is typically fulfilled by using *ad hoc* numerical differentiation techniques, which are sensitive to noise, leading to unusable state estimates. Observers are an alternative method to numerical methods. Several nonlinear observers are available in literature to estimate unmeasurable states. For instance, sliding mode observers were designed for nonlinear systems in [Canudas De Wit and Slotine \(1991\)](#), [Mohamed, Karim, and Safya \(2010\)](#) and [Slotine, Hedrick, and Misawa \(1986\)](#) based on an assumption that exact model knowledge of the dynamics is available. Model-based observers are also developed in [Lee and Khalil \(1997\)](#) and [Shin and Lee \(1999\)](#) which require a high-gain to guarantee estimation error regulation. The observers introduced in [Astolfi, Ortega, and Venkatraman \(2010\)](#) and [Lotfi and Namvar \(2010\)](#) are both applied for Lagrangian dynamic systems to estimate the

velocity. Global exponential convergence to the true velocity is obtained in [Astolfi et al. \(2010\)](#), and a global asymptotic result is proven in [Lotfi and Namvar \(2010\)](#). The result in [Astolfi et al. \(2010\)](#) is based on the immersion and invariance approach to reconstruct the unmeasurable state. The use of this approach requires the solution of a partial differential equation. Given the challenge of finding such a solution, an approximation technique is employed that introduces error in the estimation, the effects of which are dominated by high-gain terms introduced in the observer dynamics. In [Lotfi and Namvar \(2010\)](#), the system dynamics must be expressed in a non-minimal model and feedback from force sensors are used to develop a velocity estimate. In [Adhyaru \(2012\)](#), a constrained optimal observer is developed for a nonlinear system under the assumption of exact model knowledge, where a nonquadratic performance cost function is used to impose magnitude constraints on an observer gain matrix.

The design of robust observers for uncertain nonlinear systems is considered in [Davila, Fridman, and Levant \(2005\)](#), [Dawson, Qu, and Carroll \(1992\)](#), [Vasiljevic and Khalil \(2008\)](#) and [Xian, de Queiroz, Dawson, and McIntyre \(2004\)](#). In [Davila et al. \(2005\)](#), a second-order sliding mode observer for uncertain systems using a super-twisting algorithm is developed, where a nominal model of the system is assumed to be available and estimation errors are proven to converge in finite-time to a bounded set around the origin. In [Dawson et al. \(1992\)](#), the developed observer guarantees that the state estimates exponentially converge to the actual state, if there exists a vector function satisfying a complex set of matching conditions. An asymptotic velocity observer is developed

[☆] This research is supported in part by NSF award numbers 0547448, 0901491, 1161260, and 1217908. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the sponsoring agency.

* Corresponding author. Tel.: +84 979721484.

E-mail addresses: huyendtt214@gmail.com, huyendinh@utc.edu.vn
(H.T. Dinh), r.kamalapurkar@ufl.edu (R. Kamalapurkar), sbhasin@ee.iitd.ac.in (S. Bhagat), wdixon@ufl.edu (W.E. Dixon).

in Xian et al. (2004) for general second-order systems; however, all nonlinear uncertainties in the system are damped out by a sliding-mode term resulting in high-frequency state estimates. In Vasiljevic and Khalil (2008), a high-gain derivative estimator is developed to estimate the derivative(s) of a signal in the presence of measurement noise. In the absence of noise, the derivative estimation error asymptotically converges as the observer gain grows to infinity. In contrast, the result developed in this paper yields asymptotic convergence with bounded gains.

Neural networks (NN) and fuzzy logic systems provide an effective approximation method that facilitates new observer designs, improving and complementing the base of conventional observer design approaches. For example, the approaches in Boulkroune, Tadjine, MSaad, and Farza (2008), Choi and Farrell (1999), Kim and Lewis (1999), Park and Park (2003) and Vargas and Hemerly (2001) use the universal approximation property in adaptive observer designs. However, estimation errors in Boulkroune et al. (2008), Choi and Farrell (1999), Kim and Lewis (1999), Park and Park (2003) and Vargas and Hemerly (2001) are only guaranteed to be bounded due to function reconstruction errors resulting from the NN or fuzzy system.

The challenge to obtain asymptotic estimation stems from the fact that to robustly account for disturbances, feedback of the unmeasurable error and its estimate are required. Typically, feedback of the unmeasurable error is obtained by taking the derivative of the measurable state and manipulating the resulting dynamics (e.g., this is the approach used in methods such as Kim & Lewis, 1999 and Xian et al., 2004). However, such an approach provides a linear feedback term of the unmeasurable state. Hence, a sliding mode term could not be simply added to the NN structure of the result in Kim and Lewis (1999), for example, to yield an asymptotic result, because it would require the signum of the unmeasurable state. It is unclear how such a nonlinear function of the unmeasurable state can be injected in the closed-loop error system using traditional methods. Likewise, it is not clear how to simply add an NN-based feedforward estimation of the nonlinearities in results such as Xian et al. (2004) because of the need to inject nonlinear functions of the unmeasurable state.

The approach used in this paper circumvents the challenge of injecting feedback to yield an asymptotic result by using nonlinear (sliding-mode) feedback of the measurable state, and then exploiting the recurrent nature of a dynamic neural network (DNN) structure to inject terms that cancel cross terms associated with the unmeasurable state. The approach is facilitated by using the filter structure inspired by Xian et al. (2004) and a novel stability analysis. The stability analysis is based on the idea of segregating the nonlinear uncertainties into terms which can be upper-bounded by constants and terms which can be upper-bounded by states. The terms upper-bounded by states can be canceled by the linear feedback of the measurable errors, while the terms upper-bounded by constants are partially rejected by the sliding mode feedback (of the measurable state) and partially eliminated by the novel DNN-based weight update laws.

The contribution of this paper (and its preliminary version in Dinh, Kamalapurkar, Bhasin, & Dixon, 2011) is that the observer is designed for N th order uncertain nonlinear systems, where the output of the N th order system is assumed to be measurable up to $N - 1$ derivatives. The on-line approximation of the unmeasurable uncertain nonlinearities via the DNN structure should heuristically improve the performance of methods that only use high-gain feedback. Asymptotic convergence of the estimated states to the real states is proven using a Lyapunov-based analysis. The developed observer can be used separately from the controller even if the relative degree between the control input and the output is arbitrary. Simulation and experiment results on a two-link robot manipulator indicate the effectiveness of the proposed

observer when compared with the standard numerical central differentiation algorithm, along with the high-gain observer proposed in Vasiljevic and Khalil (2008) and the observer in Xian et al. (2004).

2. DNN-based observer development

Consider an N th order control affine nonlinear system given in MIMO Brunovsky form as

$$\begin{aligned} \dot{x}_1 &= x_2, \\ &\vdots \\ \dot{x}_{N-1} &= x_N, \\ \dot{x}_N &= f(x) + G(x)u + d, \end{aligned} \quad (1)$$

where $x = [x_1^T \ x_2^T \ \dots \ x_N^T]^T \in \mathbb{R}^{Nn}$ is the generalized state of the system, $u \in \mathbb{R}^m$ is the control input, $f : \mathbb{R}^{Nn} \rightarrow \mathbb{R}^n$, $G : \mathbb{R}^{Nn} \rightarrow \mathbb{R}^{n \times m}$ are unknown continuous functions, $d \in \mathbb{R}^n$ is an external disturbance. The following assumptions about the system in (1) will be utilized in the observer development.

Assumption 1. The state x is bounded, i.e., $x_i \in \mathcal{L}_\infty$, $i = 1, 2, \dots, N$, and the state x_1 is measurable up to and including the $N - 1$ th derivative, i.e. x_i , $i = 1, 2, \dots, N - 1$, are measurable.

The states x_i , $i = 1, 2, \dots, N - 1$ are available from sensor feedback. However, the higher order state x_N is not used by the subsequent development because it is not typically included as available sensor measurements. The subsequent development does not require feedback of the state x_N . Motivation of this design choice is that it reduces the need for an additional sensor or additional signal processing that is typically not included in the stability analysis. For example, to control the trajectory of robotic manipulator, many results have been developed that only require output feedback (e.g., for the second order system, only position feedback is required). Such results are motivated by the facts that typical robotic systems do not include tachometers and numerical derivatives introduce additional noise. If sufficient sensing of x_N is available, then the developed observer could be simplified (e.g., the subsequently desired dynamic filter could be eliminated) or an alternate method could be used.

Assumption 2. The unknown functions f and G , and the control input u are C^1 , and $u, \dot{u} \in \mathcal{L}_\infty$.

Assumption 3. The disturbance d is differentiable, and $d, \dot{d} \in \mathcal{L}_\infty$.

The universal approximation property states that given any continuous function $F : \mathbb{S} \rightarrow \mathbb{R}^n$, where \mathbb{S} is a compact set, there exist ideal weights such that the output of the NN, \hat{F} approximates F to an arbitrary accuracy (Hornick, 1991). Hence, the unknown functions f and G in (1) can be replaced by multi-layer NNs (MLNN) as

$$\begin{aligned} f(x) &= W_f^T \sigma_f \left(\sum_{j=1}^N V_{fj}^T x_j \right) + \varepsilon_f(x), \\ g_i(x) &= W_{gi}^T \sigma_{gi} \left(\sum_{j=1}^N V_{gij}^T x_j \right) + \varepsilon_{gi}(x), \end{aligned} \quad (2)$$

where $W_f \in \mathbb{R}^{L_f+1 \times n}$, $V_{fj} \in \mathbb{R}^{n \times L_f}$ are unknown ideal constant weight matrices of the MLNN having L_f hidden layer neurons, g_i is the i th column of the matrix G , $W_{gi} \in \mathbb{R}^{L_{gi}+1 \times n}$, $V_{gij} \in \mathbb{R}^{n \times L_{gi}}$ are unknown ideal constant weight matrices of the MLNN having L_{gi} hidden layer neurons, $i = 1 \dots m$, $j = 1, 2, \dots, N$, $\sigma_f : \mathbb{R}^{Nn} \rightarrow$

\mathbb{R}^{L_f+1} and $\sigma_{gi} : \mathbb{R}^{Nn} \rightarrow \mathbb{R}^{L_{gi}+1}$ defined as $\sigma_f \triangleq \sigma_f(\sum_{j=1}^N V_{fj}^T x_j)$, $\sigma_{gi} \triangleq \sigma_{gi}(\sum_{j=1}^N V_{gj}^T x_j)$ are activation functions (sigmoid, hyperbolic tangent, etc.), and $\varepsilon_f, \varepsilon_{gi} : \mathbb{R}^{Nn} \rightarrow \mathbb{R}^n$, $i = 1 \dots m$ are the function reconstruction errors. Using (2) and Assumption 2, the system in (1) can be represented as

$$\begin{aligned} \dot{x}_1 &= x_2, \\ &\vdots \\ \dot{x}_{N-1} &= x_N, \\ \dot{x}_N &= W_f^T \sigma_f + \varepsilon_f + d + \sum_{i=1}^m [W_{gi}^T \sigma_{gi} + \varepsilon_{gi}] u_i \end{aligned} \quad (3)$$

where $u_i \in \mathbb{R}$ is the i th element of the control input vector u . The following assumptions will be used in the observer development and stability analysis.

Assumption 4. The ideal NN weights are bounded by known positive constants (Lewis, Selmic, & Campos, 2002), i.e. $\|W_f\| \leq \bar{W}_f$, $\|V_{fj}\| \leq \bar{V}_{fj}$, $\|W_{gi}\| \leq \bar{W}_{gi}$, and $\|V_{gj}\| \leq \bar{V}_{gj}$, $i = 1 \dots m$, $j = 1, 2, \dots, N$, where $\|\cdot\|$ denotes the Frobenius norm for a matrix and Euclidean norm for a vector.

Assumption 5. The activation functions σ_f, σ_{gi} and their partial derivatives, $\sigma'_f, \sigma'_{gi}, \sigma''_f, \sigma''_{gi}$, $i = 1 \dots m$, are bounded (Lewis et al., 2002).

Assumption 6. The function reconstruction errors $\varepsilon_f, \varepsilon_{gi}$, and the respective first partial derivatives are bounded, with $i = 1 \dots m$ (Lewis et al., 2002).

The following multi-layer DNN architecture is proposed to observe the system in (1)

$$\begin{aligned} \dot{x}_1 &= \hat{x}_2, \\ &\vdots \\ \dot{x}_{N-1} &= \hat{x}_N, \\ \dot{x}_N &= \hat{W}_f^T \hat{\sigma}_f + \sum_{i=1}^m \hat{W}_{gi}^T \hat{\sigma}_{gi} u_i + v, \end{aligned} \quad (4)$$

where $\hat{x} = [\hat{x}_1 \ \hat{x}_2 \ \dots \ \hat{x}_N]^T \in \mathbb{R}^{Nn}$ is the state of the DNN observer, $\hat{W}_f \in \mathbb{R}^{L_f+1 \times n}$, $\hat{V}_{fj} \in \mathbb{R}^{n \times L_f}$, $\hat{W}_{gi} \in \mathbb{R}^{L_{gi}+1 \times n}$, $\hat{V}_{gj} \in \mathbb{R}^{n \times L_{gi}}$, $i = 1 \dots m$, $j = 1, 2, \dots, N$ are the weight estimates, $\hat{\sigma}_f \in \mathbb{R}^{L_f+1}$, and $\hat{\sigma}_{gi} \in \mathbb{R}^{L_{gi}+1}$ are defined as $\hat{\sigma}_f \triangleq \sigma_f(\sum_{j=1}^N \hat{V}_{fj}^T \hat{x}_j)$, $\hat{\sigma}_{gi} \triangleq \sigma_{gi}(\sum_{j=1}^N \hat{V}_{gj}^T \hat{x}_j)$, and $v \in \mathbb{R}^n$ is a function that is subsequently designed to provide robustness to function reconstruction errors and external disturbances.

Remark 1. In (4), the feedforward NN terms $\hat{W}_f \hat{\sigma}_f$, $\hat{W}_{gi} \hat{\sigma}_{gi}$ use internal feedback of the observer states \hat{x} : a DNN structure. The recurrent feedback loop in a DNN enables it to approximate dynamic systems with any arbitrary degree of accuracy (Funahashi & Nakamura, 1993; Polycarpou & Ioannou, 1991). This property motivates the DNN-based observer design. The DNN is automatically trained to estimate the system dynamics by the subsequent weight update laws, weight estimates, and filter output.

The objective is to prove that the estimated state \hat{x} converges to the system state x . To facilitate the subsequent analysis, the estimation error $\tilde{x}_1 \in \mathbb{R}^n$ is defined as

$$\tilde{x}_1 \triangleq x_1 - \hat{x}_1. \quad (5)$$

To facilitate the subsequent stability analysis and compensate for the lack of direct measurements of x_N , the following filtered

estimation errors are defined as

$$\begin{aligned} \tilde{x}_2 &\triangleq \dot{\tilde{x}}_1 + \alpha_1 \tilde{x}_1, \\ \tilde{x}_j &\triangleq \dot{\tilde{x}}_{j-1} + \alpha_{j-1} \tilde{x}_{j-1} + \tilde{x}_{j-2}, \quad j = 3, \dots, N-1 \\ r &\triangleq \dot{\tilde{x}}_{N-1} + \alpha \tilde{x}_{N-1} + \eta, \end{aligned} \quad (6)$$

where $\alpha, \alpha_1, \dots, \alpha_{N-2} \in \mathbb{R}$ are positive constant control gains, and $\eta \in \mathbb{R}^n$ is an output of the dynamic filter (Xian et al., 2004)

$$\begin{aligned} \eta &= p - (k + \alpha) \tilde{x}_{N-1}, \\ \dot{p} &= -(k + 2\alpha)p - \tilde{x}_f + ((k + \alpha)^2 + 1) \tilde{x}_{N-1}, \\ \dot{\tilde{x}}_f &= p - \alpha \tilde{x}_f - (k + \alpha) \tilde{x}_{N-1}, \\ p(0) &= (k + \alpha) \tilde{x}_{N-1}(0), \quad \tilde{x}_f(0) = 0, \end{aligned} \quad (7)$$

where $\tilde{x}_f \in \mathbb{R}^n$ is an auxiliary output of the filter, $p \in \mathbb{R}^n$ is used as an internal filter variable, and $k \in \mathbb{R}$ is a positive constant gain. The filtered estimation error r is not measurable, since the expression in (6) depends on \dot{x} .

Remark 2. The second order dynamic filter to estimate the system velocity was first proposed for the output feedback controller in Xian et al. (2004). The filter in (7) admits the filtered estimation error \tilde{x}_{N-1} as an input and produces \tilde{x}_f and η . The auxiliary signal p is utilized to only generate the signal η without involving the derivative of the estimation error $\dot{\tilde{x}}_{N-1}$ which is unmeasurable. Hence, the filter can be physically implemented. A difficulty to obtain asymptotic estimation is that the filtered estimation error r is not available for feedback. A relationship between the two filter outputs is $\eta = \dot{\tilde{x}}_f + \alpha \tilde{x}_f$, and this relationship is utilized to generate the feedback of r . By taking the time derivative of r , the term $\dot{\tilde{x}}_f$ appears implicitly inside \dot{r} . Consequently, the unmeasurable term $\dot{\tilde{x}}_N$ is introduced in a way that it can be replaced by r .

Remark 3. Several observer designs (cf. Calise, Hovakimyan, & Idan, 2001, Kim, Lewis, & Abdallah, 1997 and Lotfi & Namvar, 2010) exploit a strictly positive real (SPR) condition to show convergence, typically exploiting the Meyer–Kalman–Yakubovich lemma. Designs based on the SPR condition require the dynamic order of the observer to be large. The developed observer avoids this condition by using a dynamic filter to inject the negative feedback of $r(t)$, yielding convergence of the observer.

Taking the derivative of η and using (6) and (7) yields

$$\dot{\eta} = -(k + \alpha)r - \alpha\eta + \tilde{x}_{N-1} - \tilde{x}_f. \quad (8)$$

The closed-loop dynamics of the derivative of the filtered estimation error r in (6) is determined from (3)–(6) and (8) as

$$\begin{aligned} \dot{r} &= W_f^T \sigma_f - \hat{W}_f^T \hat{\sigma}_f + \sum_{i=1}^m [W_{gi}^T \sigma_{gi} - \hat{W}_{gi}^T \hat{\sigma}_{gi}] u_i + \varepsilon_f \\ &\quad + \sum_{i=1}^m \varepsilon_{gi} u_i + d - v + \alpha(r - \alpha \tilde{x}_{N-1} - \eta) \\ &\quad - (k + \alpha)r - \alpha\eta + \tilde{x}_{N-1} - \tilde{x}_f. \end{aligned} \quad (9)$$

Based on the subsequent analysis, the robust disturbance rejection term v is designed to inject cross terms to account for related terms in the stability analysis and a sliding mode term to deal with the disturbances in the system as

$$v = -[\gamma(k + \alpha) + 2\alpha]\eta + (\gamma - \alpha^2)\tilde{x}_{N-1} + \beta_1 \text{sgn}(\tilde{x}_{N-1} + \tilde{x}_f), \quad (10)$$

where $\gamma, \beta_1 \in \mathbb{R}$ are positive constant control gains. By adding and subtracting $W_f^T \sigma_f (\sum_{j=1}^N \hat{V}_{fj}^T \hat{x}_j) + \hat{W}_f^T \hat{\sigma}_f (\sum_{j=1}^N \hat{V}_{fj}^T \hat{x}_j) + \sum_{i=1}^m$

from (10), the expression in (9) can be rewritten as

$$\dot{r} = \tilde{N} + N - kr - \beta_1 \text{sgn}(\tilde{x}_{N-1} + \tilde{x}_f) + \gamma(k + \alpha)\eta - \gamma\tilde{x}_{N-1}, \quad (11)$$

where the auxiliary function $\tilde{N} \in \mathbb{R}^n$ is defined as

$$\begin{aligned} \tilde{N} &\triangleq \hat{W}_f^T \left[\sigma_f \left(\sum_{j=1}^N \hat{V}_{f_j}^T x_j \right) - \hat{\sigma}_f \right] + \tilde{x}_{N-1} - \tilde{x}_f \\ &+ \sum_{i=1}^m \hat{W}_{gi}^T \left[\sigma_{gi} \left(\sum_{j=1}^N \hat{V}_{gi_j}^T x_j \right) - \hat{\sigma}_{gi} \right] u_i, \end{aligned} \quad (12)$$

and $N \in \mathbb{R}^n$ is segregated into two parts as

$$N \triangleq N_1 + N_2. \quad (13)$$

In (13), $N_1, N_2 \in \mathbb{R}^n$ are defined as

$$\begin{aligned}
N_1 &\triangleq \tilde{W}_f^T \sigma_f' \left[\sum_{j=1}^N \tilde{V}_{fj}^T x_j \right] + W_f^T O \left(\sum_{j=1}^N \tilde{V}_{fj}^T x_j \right)^2 \\
&\quad + \sum_{i=1}^m \varepsilon_{gi} u_i + \varepsilon_f + d + \sum_{i=1}^m \tilde{W}_{gi}^T \sigma_{gi}' \left[\sum_{j=1}^N \tilde{V}_{gj}^T x_j \right] u_i \\
&\quad + \sum_{i=1}^m W_{gi}^T O \left(\sum_{j=1}^N \tilde{V}_{gj}^T x_j \right)^2 u_i, \\
N_2 &\triangleq \tilde{W}_f^T \sigma_f \left(\sum_{j=1}^N \hat{V}_{fj}^T x_j \right) + \sum_{i=1}^m \tilde{W}_{gi}^T \sigma_{gi} \left(\sum_{j=1}^N \hat{V}_{gj}^T x_j \right) u_i \\
&\quad + \hat{W}_f^T \sigma_f' \left[\sum_{j=1}^N \tilde{V}_{fj}^T x_j \right] + \sum_{i=1}^m \hat{W}_{gi}^T \sigma_{gi}' \left[\sum_{j=1}^N \tilde{V}_{gj}^T x_j \right] u_i,
\end{aligned} \tag{14}$$

where $\tilde{W}_f \triangleq W_f - \hat{W}_f \in \mathbb{R}^{L_f+1 \times n}$, $\tilde{V}_{f_j} \triangleq V_{f_j} - \hat{V}_{f_j} \in \mathbb{R}^{n \times L_f}$, $\tilde{W}_{gi} \triangleq W_{gi} - \hat{W}_{gi} \in \mathbb{R}^{L_{gi}+1 \times n}$, $\tilde{V}_{gi_j} \triangleq V_{gi_j} - \hat{V}_{gi_j} \in \mathbb{R}^{n \times L_{gi}}$, $i = 1 \dots m$, $j = 1, 2, \dots, N$ are the estimate mismatches for the ideal NN weights; $O(\sum_{j=1}^N \tilde{V}_{f_j}^T x_j)^2 \in \mathbb{R}^{L_f+1}$, $O(\sum_{j=1}^N \tilde{V}_{gi_j}^T x_j)^2 \in \mathbb{R}^{L_{gi}+1}$ are the higher-order terms in the Taylor series approximation of the vector functions σ_f , σ_{gi} in the neighborhood of $\sum_{j=1}^N \hat{V}_{f_j}^T x_j$ and $\sum_{j=1}^N \hat{V}_{gi_j}^T x_j$, respectively, as

$$\begin{aligned}\sigma_f &= \sigma_f \left(\sum_{j=1}^N \hat{V}_{fj}^T x_j \right) + \sigma'_f \left[\sum_{j=1}^N \tilde{V}_{fj}^T x_j \right] + O \left(\sum_{j=1}^N \tilde{V}_{fj}^T x_j \right)^2, \\ \sigma_{gi} &= \sigma_{gi} \left(\sum_{i=1}^N \hat{V}_{gi}^T x_j \right) + \sigma'_{gi} \left[\sum_{i=1}^N \tilde{V}_{gi}^T x_j \right] + O \left(\sum_{i=1}^N \tilde{V}_{gi}^T x_j \right)^2, \quad (15)\end{aligned}$$

where the terms σ'_f , σ'_{gi} are defined as $\sigma'_f \triangleq \sigma'_f(\sum_{j=1}^N \hat{V}_{fj}^T x_j) = d\sigma_f(\theta)/d\theta|_{\theta=\sum_{j=1}^N \hat{V}_{fj}^T x_j}$ and $\sigma'_{gi} \triangleq \sigma'_{gi}(\sum_{j=1}^N \hat{V}_{gj}^T x_j) = d\sigma_{gi}(\theta)/d\theta|_{\theta=\sum_{j=1}^N \hat{V}_{gj}^T x_j}$. To facilitate the subsequent analysis, an auxiliary function $\hat{N}_2 \in \mathbb{R}^n$ is defined by replacing the terms x_j in N_2 by \hat{x}_j , $j = 1, 2, \dots, N$, respectively.

The weight update laws for the DNN in (4) are developed based on the subsequent stability analysis as

$$\begin{aligned}
 \dot{\hat{W}}_f &= \text{proj}[\Gamma_{wf} \hat{\sigma}_f (\tilde{x}_{N-1} + \tilde{x}_f)^T], \\
 \dot{\hat{W}}_{f_j} &= \text{proj}[\Gamma_{vf_j} \hat{x}_j (\tilde{x}_{N-1} + \tilde{x}_f)^T \hat{W}_f^T \hat{\sigma}'_f], \quad j = 1..N \\
 \dot{\hat{W}}_{gi} &= \text{proj}[\Gamma_{wgi} \hat{\sigma}_{gi} u_i (\tilde{x}_{N-1} + \tilde{x}_f)^T], \quad i = 1..m \\
 \dot{\hat{V}}_{gi} &= \text{proj}[\Gamma_{vgi} \hat{x}_i (\tilde{x}_{N-1} + \tilde{x}_f)^T \hat{W}_{gi}^T \hat{\sigma}'_{gi}], \quad i = 1..m,
 \end{aligned} \tag{16}$$

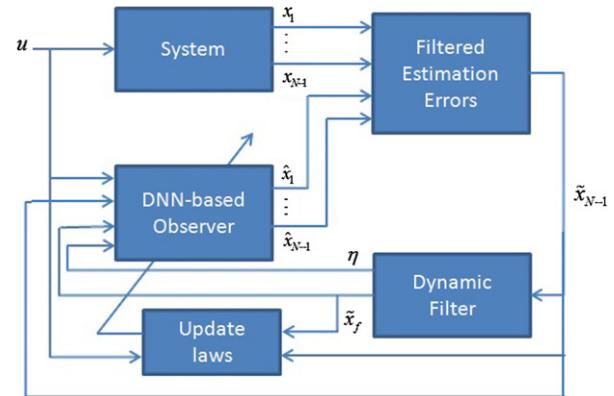


Fig. 1. The architecture of the DNN-based observer.

where $\Gamma_{wf} \in \mathbb{R}^{(L_f+1) \times (L_f+1)}$, $\Gamma_{wgi} \in \mathbb{R}^{(L_{gi}+1) \times (L_{gi}+1)}$, $\Gamma_{vf_j}, \Gamma_{vgi_j} \in \mathbb{R}^{n \times n}$, are constant symmetric positive-definite adaptation gains, the terms $\hat{\sigma}'_f, \hat{\sigma}'_{gi}$ are defined as $\hat{\sigma}'_f \triangleq \sigma'_f(\sum_{j=1}^N \hat{V}_{fj}^T \hat{x}_j) = d\sigma_f(\theta)/d\theta|_{\theta=\sum_{j=1}^N \hat{V}_{fj}^T \hat{x}_j}$, $\hat{\sigma}'_{gi} \triangleq \sigma'_{gi}(\sum_{j=1}^N \hat{V}_{gij}^T \hat{x}_j) = d\sigma_{gi}(\theta)/d\theta|_{\theta=\sum_{j=1}^N \hat{V}_{gij}^T \hat{x}_j}$, and $\text{proj}(\cdot)$ is a smooth projection operator (see Section 4.3 of Dixon, Behal, Dawson, & Nagarkatti, 2003, or Appendix E of Krstic, Kokotovic, & Kanellakopoulos, 1995 for details) used to guarantee that the weight estimates $\hat{W}_f, \hat{V}_{fj}, \hat{W}_{gi}$, and \hat{V}_{gij} remain bounded.

The architecture of the observer is shown in Fig. 1.

Using (5)–(7), Assumptions 2–5, the $\text{proj}(\cdot)$ algorithm in (16) and the Mean Value Theorem, the auxiliary function \tilde{N} in (12) can be upper-bounded as

$$\|\tilde{N}\| \leq \zeta_1 \|z\|, \quad (17)$$

where $z \in \mathbb{R}^{(N+2)n}$ is defined as

$$z \triangleq [\tilde{x}_1^T \dots \tilde{x}_{N-1}^T \tilde{x}_f^T \eta^T r^T]^T. \quad (18)$$

Based on (5)–(7), Assumptions 1–6, the Taylor series expansion in (15) and the weight update laws in (16), the following bounds can be developed:

$$\|N_1\| \leq \xi_2, \|N_2\| \leq \xi_3, \|\tilde{N}_2\| \leq \xi_5 \|z\|,$$

$$\|\dot{N}\| \leq \zeta_4 + \rho(\|z\|) \|z\|, \quad (19)$$

where $\zeta_i \in \mathbb{R}$, $i = 1 \dots 5$, are computable positive constants, $\rho \in \mathbb{R}$ is a positive, globally invertible, non-decreasing function, and $\tilde{N}_2 \triangleq N_2 - \hat{N}_2$.

To facilitate the subsequent stability analysis, let $y \in \mathbb{R}^{(N+2)n+2}$ be defined as

$$y \triangleq \begin{bmatrix} z^T & \sqrt{P} & \sqrt{Q} \end{bmatrix}^T, \quad (20)$$

and let $\mathcal{D} \subset \mathbb{R}^{(N+2)n+2}$ be the open and connected set $\mathcal{D} \triangleq \left\{ y \in \mathbb{R}^{(N+2)n+2} \mid \|y\| < \rho^{-1}(\lambda - \frac{\zeta_1^2}{4\sqrt{2}k_2}) \right\}$. In (20), the auxiliary function $P \in \mathbb{R}$ is a generalized Filippov solution to the differential equation

$$\dot{P} \triangleq -r^T(N_1 - \beta_1 \text{sgn}(\tilde{x}_{N-1} + \tilde{x}_f)) - (\dot{\tilde{x}}_{N-1} + \dot{\tilde{x}}_f)^T N_2, +\sqrt{2}\rho(\|z\|)\|z\|^2, \quad (21)$$

$$P(0) \triangleq \beta_1 \sum_{i=1}^n \left| \tilde{x}_{N-1_i}(0) + \tilde{x}_{f_i}(0) \right| - (\tilde{x}_{N-1}(0) + \tilde{x}_f(0))^T N(0),$$

where the subscript $i = 1, 2, \dots, n$ denotes the i th element of $\tilde{x}_{N-1}(0)$ or $\tilde{x}_f(0)$, and $\beta_1 \in \mathbb{R}$ is a positive constant chosen

according to the sufficient condition

$$\beta_1 > \max \left(\zeta_2 + \zeta_3, \zeta_2 + \frac{\zeta_4}{\alpha} \right), \quad (22)$$

where ζ_i , $i = 2, 3, 4$ are introduced in (19). Provided the sufficient condition in (22) is satisfied, $P \geq 0$ (see Bhasin, Kamalapurkar, Dinh, & Dixon, 2013, Dinh, Bhasin, & Dixon, 2010). The auxiliary function $Q \in \mathbb{R}$ in (20) is defined as

$$Q \triangleq \frac{\alpha}{2} \left[\sum_{i=1}^m \text{tr}(\tilde{W}_{gi}^T \Gamma_{wg_i}^{-1} \tilde{W}_{gi}) + \sum_{j=1}^N \text{tr}(\tilde{V}_{fj}^T \Gamma_{vf_j}^{-1} \tilde{V}_{fj}) \right. \\ \left. + \text{tr}(\tilde{W}_f^T \Gamma_{wf}^{-1} \tilde{W}_f) + \sum_{j=1}^N \sum_{i=1}^m \text{tr}(\tilde{V}_{gij}^T \Gamma_{vgij}^{-1} \tilde{V}_{gij}) \right] \quad (23)$$

where $\text{tr}(\cdot)$ denotes the trace of a matrix. Since the gains Γ_{wf} , Γ_{wg_i} , Γ_{vf_j} , Γ_{vgij} are symmetric, positive-definite matrices, $Q \geq 0$.

3. Lyapunov stability analysis for DNN-based observer

Theorem 1. *The DNN-based observer proposed in (4) along with its weight update laws in (16) ensures semi-global asymptotic estimation in the sense that*

$$\|\tilde{x}_j\| \rightarrow 0 \quad \text{and} \quad \|x_N - \hat{x}_N\| \rightarrow 0 \quad \text{as } t \rightarrow \infty,$$

with $j = 1 \dots (N-1)$, provided the control gain $k = k_1 + k_2$ introduced in (7) is selected sufficiently large based on the initial conditions of the states,¹ the gain condition in (22) is satisfied, and the following sufficient conditions are satisfied:

$$\alpha_j, \alpha, k_1 > \frac{1}{2}, \quad \gamma > \frac{2\alpha^2\zeta_5^2 + 1}{2\alpha - 1}, \quad \text{and} \quad \lambda > \frac{\zeta_1^2}{4\sqrt{2}k_2} \quad (24)$$

where

$$\lambda \triangleq \frac{1}{\sqrt{2}} \left[\min \left(\alpha\gamma - \frac{\gamma}{2} - \alpha^2\zeta_5^2, \gamma \left(\alpha_j - \frac{1}{2} \right), k_1 \right) - \frac{1}{2} \right], \quad (25)$$

and ζ_1, ζ_5 are introduced in (17) and (19), respectively.

Proof. Consider the candidate Lyapunov function $V_L : \mathcal{D} \rightarrow \mathbb{R}$, which is a Lipschitz continuous positive definite function defined as

$$V_L \triangleq \frac{\gamma}{2} \sum_{j=1}^{N-1} \tilde{x}_j^T \tilde{x}_j + \frac{\gamma}{2} \tilde{x}_f^T \tilde{x}_f + \frac{\gamma}{2} \eta^T \eta + \frac{1}{2} r^T r + P + Q, \quad (26)$$

which satisfies the following inequalities:

$$U_1(y) \leq V_L(y) \leq U_2(y), \quad (27)$$

where $U_1, U_2 : \mathbb{R}^{(N+2)n+2} \rightarrow \mathbb{R}$ are continuous positive definite functions defined as $U_1(y) \triangleq \min(\frac{\gamma}{2}, \frac{1}{2}) \|y\|^2$, $U_2(y) \triangleq \max(\frac{\gamma}{2}, 1) \|y\|^2$.

Let $\dot{y} = h$ represent the closed-loop differential equations in (6)–(8), (11), (16) and (21), where $h \in \mathbb{R}^{(N+2)n+2}$ denotes the right-hand side of the closed-loop error signals. Using Filippov's theory of differential inclusions (Aubin & Frankowska, 2008; Filippov, 1964, 1988; Smirnov, 2002), the existence of solutions can be established for $\dot{y} \in K[h](y)$, where $K[h] \triangleq \cap_{\delta>0} \cap_{\mu M=0}$

$\overline{\text{co}} h(B(y, \delta) \setminus M)$, where $\cap_{\mu M=0}$ denotes the intersection of all sets M of Lebesgue measure zero, $\overline{\text{co}}$ denotes convex closure, and $B(y, \delta) = \{w \in \mathbb{R}^{(N+2)n+2} \mid \|y - w\| < \delta\}$. The generalized time derivative of (26) exists almost everywhere (a.e.), i.e. for almost all $t \in [t_0, t_f]$, and $\dot{V}_L \in \text{a.e. } \dot{\tilde{V}}_L$, where $\dot{\tilde{V}}_L = \bigcap_{\xi \in \partial V_L(y)} \dot{\xi}^T K[\Psi]^T \partial V_L$ is the generalized gradient of V_L (Clarke, 1990), and $\Psi \triangleq [\dot{\tilde{x}}_1^T \dots \dot{\tilde{x}}_{N-1}^T \dot{\tilde{x}}_f^T \dot{\eta}^T \dot{r}^T \frac{1}{2} P^{-\frac{1}{2}} \dot{P}^{\frac{1}{2}} Q^{-\frac{1}{2}} \dot{Q}]$. Since V_L is continuously differentiable, $\dot{\tilde{V}}_L$ can be simplified as (Shevitz & Paden, 1994) $\dot{\tilde{V}}_L = \nabla V_L^T K[\Psi]^T = [\gamma \tilde{x}_1^T \dots \gamma \tilde{x}_{N-1}^T \gamma \tilde{x}_f^T \gamma \eta^T \dot{r}^T 2P^{\frac{1}{2}} 2Q^{\frac{1}{2}}] K[\Psi]^T$. Using the calculus for $K[\cdot]$ from Paden and Sastry (1987, Theorem 1, Properties 2, 5, 7), and substituting the dynamics from (6)–(8), (11), (21) and (23) and adding and subtracting $\alpha(\tilde{x}_{N-1} + \tilde{x}_f)^T \hat{N}_2$ and using (14), $\dot{\tilde{V}}_L$ can be rewritten as

$$\begin{aligned} \dot{\tilde{V}}_L \subset & \gamma \tilde{x}_1^T (\tilde{x}_2 - \alpha_1 \tilde{x}_1) + \gamma \tilde{x}_{N-1}^T (r - \alpha \tilde{x}_{N-1} - \eta) \\ & + \gamma \tilde{x}_f^T (\eta - \alpha \tilde{x}_f) + \gamma \sum_{j=2}^{N-2} \tilde{x}_j^T (\tilde{x}_{j+1} - \alpha_j \tilde{x}_j - \tilde{x}_{j-1}) \\ & + \gamma \eta^T [-(k + \alpha)r - \alpha \eta] \\ & + \gamma \eta^T [\tilde{x}_{N-1} - \tilde{x}_f] - \alpha(\tilde{x}_{N-1} + \tilde{x}_f)^T \hat{N}_2 \\ & - kr^T r - \gamma r^T \tilde{x}_{N-1} \\ & + r^T [\tilde{N} + N - \beta_1 K[\text{sgn}(\tilde{x}_{N-1} + \tilde{x}_f)] + \gamma(k + \alpha)\eta] \\ & - r^T (N_1 - \beta_1 K[\text{sgn}(\tilde{x}_{N-1} + \tilde{x}_f)]) \\ & - (\dot{\tilde{x}}_{N-1} + \dot{\tilde{x}}_f)^T \hat{N}_2 \\ & + \sqrt{2\rho(\|z\|)} \|z\|^2 + \alpha(\tilde{x}_{N-1} + \tilde{x}_f)^T \\ & \times \left\{ \hat{W}_f^T \hat{\sigma}_f' \left[\sum_{j=1}^N \tilde{V}_{fj}^T \hat{x}_j \right] + \tilde{W}_f^T \hat{\sigma}_f' \right. \\ & \left. + \sum_{i=1}^m \tilde{W}_{gi}^T \hat{\sigma}_{gi} u_i + \sum_{i=1}^m \hat{W}_{gi}^T \hat{\sigma}'_{gi} \left[\sum_{j=1}^N \tilde{V}_{gij}^T \hat{x}_j \right] u_i \right\} \\ & - \alpha \left[\text{tr}(\tilde{W}_f^T \Gamma_{wf}^{-1} \dot{\tilde{W}}_f) + \sum_{j=1}^N \text{tr}(\tilde{V}_{fj}^T \Gamma_{vf_j}^{-1} \dot{\tilde{V}}_{fj}) \right. \\ & \left. + \sum_{i=1}^m \text{tr}(\tilde{W}_{gi}^T \Gamma_{wg_i}^{-1} \dot{\tilde{W}}_{gi}) + \sum_{i=1}^m \sum_{j=1}^N \text{tr}(\tilde{V}_{gij}^T \Gamma_{vgij}^{-1} \dot{\tilde{V}}_{gij}) \right]. \end{aligned} \quad (28)$$

Using the fact that $K[\text{sgn}(\tilde{x}_{N-1} + \tilde{x}_f)] = \text{SGN}(\tilde{x}_{N-1} + \tilde{x}_f)$ (Paden & Sastry, 1987), such that $\text{SGN}(\tilde{x}_{N-1_i} + \tilde{x}_f_i) = 1$ if $(\tilde{x}_{N-1_i} + \tilde{x}_f_i) > 0$, $[-1, 1]$ if $(\tilde{x}_{N-1_i} + \tilde{x}_f_i) = 0$, and -1 if $(\tilde{x}_{N-1_i} + \tilde{x}_f_i) < 0$ (the subscript i denotes the i th element), the set in (28) reduces to the scalar inequality, since the right-hand-side (RHS) of (28) is continuous a.e., i.e., the RHS is continuous except for the Lebesgue measure zero set of times when² $r^T \text{SGN}(\tilde{x}_{N-1} + \tilde{x}_f) - r^T \text{SGN}(\tilde{x}_{N-1} + \tilde{x}_f) = 0$. Substituting the weight update laws in (16) and canceling

² Let $\Phi \triangleq \tilde{x}_{N-1} + \tilde{x}_f$. The set of times $\Lambda \triangleq \{t \in [0, \infty) : r(t)^T K[\text{sgn}(\Phi(t))] - r(t)^T K[\text{sgn}(\Phi(t))] \neq \{0\} \subset [0, \infty)$ is equal to the set of times $\{t : \Phi(t) = 0 \wedge r(t) \neq 0\}$. Using the fact that $\eta = \dot{\tilde{x}}_f + \alpha \tilde{x}_f$, r can be expressed as $r = \dot{\Phi} + \alpha \Phi$. Thus, the set Λ can also be represented by $\{t : \Phi(t) = 0 \wedge \dot{\Phi}(t) \neq 0\}$. Since $\dot{\Phi} : [0, \infty) \rightarrow \mathbb{R}^n$ is continuously differentiable, it can be shown that the set of time instances $\{t : \Phi(t) = 0 \wedge \dot{\Phi}(t) \neq 0\}$ is isolated, and thus, measure zero; hence, Λ is measure zero.

¹ See the subsequent proof.

common terms yields

$$\begin{aligned} \dot{V}_L &\stackrel{\text{a.e.}}{\leq} -\gamma \sum_{j=1}^{N-2} \alpha_j \tilde{x}_j^T \tilde{x}_j - \gamma \alpha \tilde{x}_{N-1}^T \tilde{x}_{N-1} + \gamma \tilde{x}_{N-2}^T \tilde{x}_{N-1} \\ &\quad - \gamma \alpha \tilde{x}_f^T \tilde{x}_f - \gamma \alpha \eta^T \eta - kr^T r + r^T \tilde{N} \\ &\quad + \alpha (\tilde{x}_{N-1} + \tilde{x}_f)^T \tilde{N}_2 + \sqrt{2} \rho(\|z\|) \|z\|^2. \end{aligned} \quad (29)$$

Using (17), (19), the facts that

$$\begin{aligned} \gamma \tilde{x}_{N-2}^T \tilde{x}_{N-1} &\leq \frac{\gamma}{2} \|\tilde{x}_{N-1}\|^2 + \frac{\gamma}{2} \|\tilde{x}_{N-2}\|^2 \\ \alpha \zeta_5 \|\tilde{x}_{N-1} + \tilde{x}_f\| \|z\| &\leq \alpha^2 \zeta_5^2 \|\tilde{x}_{N-1}\|^2 + \alpha^2 \zeta_5^2 \|\tilde{x}_f\|^2 + \frac{1}{2} \|z\|^2, \end{aligned}$$

substituting $k = k_1 + k_2$, and completing the squares, the expression in (29) can be further bounded as

$$\begin{aligned} \dot{V}_L &\stackrel{\text{a.e.}}{\leq} -\gamma \sum_{j=1}^{N-2} \left(\alpha_j - \frac{1}{2} \right) \|\tilde{x}_j\|^2 - \alpha(\gamma - \alpha \zeta_5^2) \|\tilde{x}_f\|^2 \\ &\quad - \left(\alpha \gamma - \frac{\gamma}{2} - \alpha^2 \zeta_5^2 \right) \|\tilde{x}_{N-1}\|^2 - \alpha \gamma \|\eta\|^2 - k_1 \|r\|^2 \\ &\quad + \left(\frac{1}{2} + \frac{\zeta_1^2}{4k_2} + \sqrt{2} \rho(\|z\|) \right) \|z\|^2. \end{aligned}$$

Provided the sufficient conditions in (24) are satisfied, the following inequality can be developed as:

$$\dot{V}_L \stackrel{\text{a.e.}}{\leq} -\sqrt{2} \left(\lambda - \frac{\zeta_1^2}{4\sqrt{2}k_2} - \rho(\|z\|) \right) \|z\|^2 \stackrel{\text{a.e.}}{\leq} -U(y) \quad \forall y \in \mathcal{D}, \quad (30)$$

where λ is defined in (25), and $U(y) = c \|z\|^2$, for some positive constant c , is a continuous positive semi-definite function which is defined on \mathcal{D} . The inequalities in (27) and (30) show that $V_L \in \mathcal{L}_\infty$; hence, $\tilde{x}_j, \tilde{x}_f, \eta, r, P$ and $Q \in \mathcal{L}_\infty$, with $\forall j = 1 \dots N-1$; (6)–(8) are used to show that $\tilde{x}_j, \tilde{x}_f, \eta \in \mathcal{L}_\infty$, with $\forall j = 1 \dots N-1$. Since $x_j \in \mathcal{L}_\infty$ by Assumption 1, $\hat{x}_j \in \mathcal{L}_\infty$ using (5). Since $\tilde{x}_j, \tilde{x}_f, \eta \in \mathcal{L}_\infty$, using (10), $v \in \mathcal{L}_\infty$. Since $W_f, W_{gi}, \sigma_f, \sigma_{gi}, \varepsilon_f, \varepsilon_{gi} \in \mathcal{L}_\infty$, $i = 1 \dots m$, by Assumptions 4–6, the control input u and the disturbance d are bounded by Assumptions 2–3, and $\hat{W}_f, \hat{W}_{gi} \in \mathcal{L}_\infty$, $i = 1 \dots m$, by the use of the proj(\cdot) algorithm, from (9), $\dot{r} \in \mathcal{L}_\infty$; then $\dot{z} \in \mathcal{L}_\infty$, by using (18). Let $S \subset \mathcal{D}$ denote a set defined as

$$S \triangleq \left\{ y \in \mathcal{D} \mid U_2(y) < \varepsilon_1 \left(\rho^{-1} \left(\lambda - \frac{\zeta_1^2}{4\sqrt{2}k_2} \right) \right)^2 \right\}. \quad (31)$$

From (30), (Fischer, Kamalapurkar, & Dixon, 2013, Corollary 1) can be invoked to show that $c \|z\|^2 \rightarrow 0$ as $t \rightarrow \infty$, $\forall y(0) \in S$. Based on the definition of z the following result can be proven:

$$\|\tilde{x}_j\|, \|\eta\|, \|r\| \rightarrow 0 \quad \text{as } t \rightarrow \infty \quad \forall y(0) \in S, \quad \forall j = 1 \dots N-1.$$

From (6), it can be further shown that

$$\|x_N - \hat{x}_N\| \rightarrow 0 \quad \text{as } t \rightarrow \infty \quad \forall y(0) \in S.$$

Note that the region of attraction in (31) can be made arbitrarily large to include any initial condition by increasing the control gains k , γ , α_j and α (i.e., a semi-global type of stability result). \square

4. Experiment and simulation results

Experiments and simulations on a two-link revolute, direct drive robot manipulator are performed to compare the proposed method with several other estimation methods. The following

dynamics of the testbed is considered for the simulations and experiments:

$$M(x)\ddot{x} + V_m(x, \dot{x})\dot{x} + F_d\dot{x} + F_s(\dot{x}) = u, \quad (32)$$

where $x = [x_1 \ x_2]^T$ are the angular positions (rad) and $\dot{x} = [\dot{x}_1 \ \dot{x}_2]^T$ are the angular velocities (rad/s) of the two links respectively. In (32), M is the inertia matrix and V_m is the centripetal–Coriolis matrix, defined as

$$\begin{aligned} M(x) &\triangleq \begin{bmatrix} p_1 + 2p_3c_2 & p_2 + p_3c_2 \\ p_2 + p_3c_2 & p_2 \end{bmatrix}, \\ V_m(x, \dot{x}) &\triangleq \begin{bmatrix} -p_3s_2\dot{x}_2 & -p_3s_2(\dot{x}_1 + \dot{x}_2) \\ p_3s_2\dot{x}_1 & 0 \end{bmatrix}. \end{aligned} \quad (33)$$

In (32) and (33), parameters for simulation are selected as the best-guess of the testbed model as $p_1 = 3.473 \text{ kg m}^2$, $p_2 = 0.196 \text{ kg m}^2$, $p_3 = 0.242 \text{ kg m}^2$, $c_2 = \cos(x_2)$, $s_2 = \sin(x_2)$. $F_d = \text{diag}\{5.3, 1.1\} \text{ N m s}$ and $F_s(\dot{x}) = \text{diag}\{8.45 \tanh(\dot{x}_1), 2.35 \tanh(\dot{x}_2)\} \text{ N m}$ are the models for dynamic and static friction, respectively. The system in (32) can be rewritten as

$$\ddot{x} = f + Gu + d,$$

where $d \in \mathbb{R}^2$ is the additive exogenous disturbance and $f : \mathbb{R}^4 \rightarrow \mathbb{R}^2$, and $G : \mathbb{R}^4 \rightarrow \mathbb{R}^4$ are defined as $f \triangleq M^{-1}(-V_m - F_d)\dot{x} - F_s$, $G \triangleq M^{-1}$.

The proportional derivative (PD) controller given by $u = 20(x - x_d) + 10(\dot{x} - \dot{x}_d)$ to track a desired trajectory $x_d(t) = [0.5 \sin(2t) \ 0.5 \cos(2t)]^T$ is applied, where the angular velocity \dot{x} , used only in the control law, is determined numerically by a standard backwards difference algorithm.

The objective is to design an observer \hat{x} to asymptotically estimate the angular velocities \dot{x} using only the measurements of the angular positions x . The control gains for the experiment are selected as $k = 7$, $\alpha = 7$, $\gamma = 8$, $\beta_1 = 6$, and $\Gamma_{wf} = \Gamma_{wg1} = \Gamma_{wg2} = 3\mathbb{I}_{8 \times 8}$, $\Gamma_{vf} = \Gamma_{vg1} = \Gamma_{vg2} = 3\mathbb{I}_{2 \times 2}$, where $\mathbb{I}_{n \times n}$ denotes an identity matrix of appropriate dimensions. The NNs are designed to have seven hidden layer neurons and the NN weights are initialized as uniformly distributed random numbers in the interval $[-1, 1]$. The initial conditions of the system and the identifier are selected as $x_0 = [0 \ 0]^T$, $\dot{x}_0 = [0 \ 0]^T$ and $\hat{x}_0 = \dot{\hat{x}}_0 = [0, 0]^T$, respectively.

A global asymptotic velocity observer for uncertain nonlinear systems was developed by Xian et al. (2004) as

$$\dot{\hat{x}} = p + K_0 \tilde{x}, \quad \dot{p} = K_1 \text{sgn}(\tilde{x}) + K_2 \tilde{x},$$

and a high gain (HG) observer that is asymptotic as the gain goes to infinity was developed in Vasiljevic and Khalil (2008) as

$$\dot{\hat{x}} = z_h + \frac{\alpha_{h1}}{\varepsilon_{h1}} \tilde{x}, \quad \dot{z}_h = \frac{\alpha_{h2}}{\varepsilon_{h2}} \tilde{x}.$$

Both these designs are based on a purely robust feedback strategy. One of the contributions of this work is the addition of a feed-forward adaptive component to compensate for the uncertain dynamics. To gauge the benefit of this approach, the proposed observer is compared with the observers in Vasiljevic and Khalil (2008) and Xian et al. (2004). Control gains for the observer in Xian et al. (2004) are selected as $K_0 = 10$, $K_1 = 6$, and $K_2 = 10$, and control gains for the HG observer in Vasiljevic and Khalil (2008) are selected as $\alpha_{h1} = 0.6$, $\alpha_{h2} = 25$, $\varepsilon_{h1} = 0.01$, and $\varepsilon_{h2} = 0.015$. To make the comparison feasible, the gains of all observers are tuned to get the steady state RMS of position estimation errors to be approximately equal to 0.17 for a settling time of 1 s. The experiment results for the velocity estimators in Vasiljevic and Khalil (2008) and Xian et al. (2004), and the proposed method are compared with the central difference algorithm. The experiment results are shown in Fig. 2(a)–(d). The velocity estimates of the

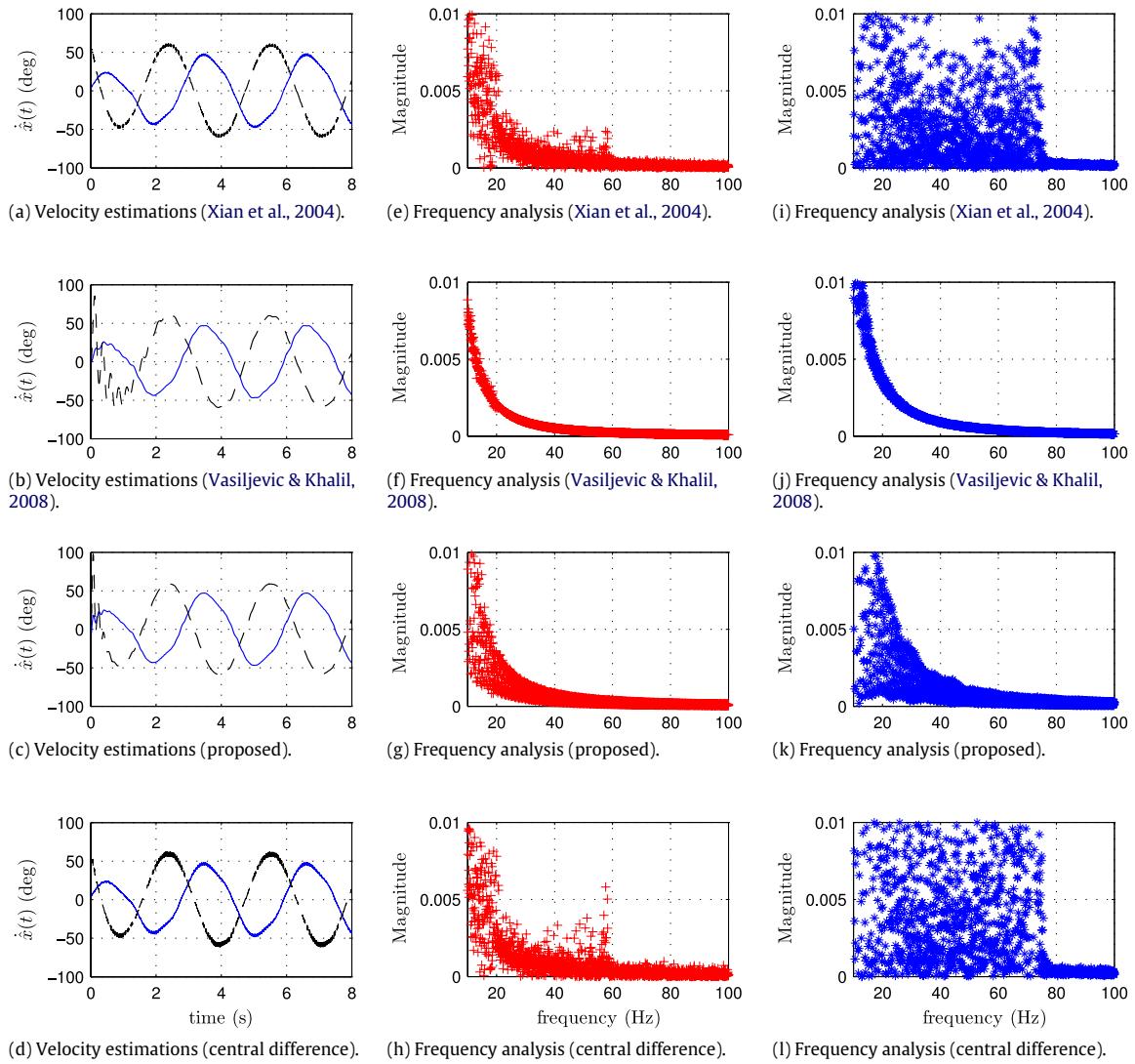


Fig. 2. Velocity estimate $\dot{\bar{x}}$ using (a) Xian et al. (2004), (b) Vasiljevic and Khalil (2008), (c) the proposed method, and (d) the center difference method on a two-link experiment testbed (solid line: Link 1, dashed line: Link 2). The other figures (e)–(l) indicate the respective frequency analysis of velocity estimation $\dot{\bar{x}}$ (plus marker: Link 1, asterisk marker: Link 2).

Table 1

Transient ($t = 0$ – 1 s) and steady state ($t = 1$ – 10 s) velocity estimation errors $\dot{\bar{x}}$ for different velocity estimation methods in presence of noise 50 dB.

	Central difference	Method in Xian et al. (2004)	Method in Vasiljevic and Khalil (2008)	Proposed
Transient RMS error	66.2682	0.1780	0.1040	0.1309
Steady state RMS error	8.1608	0.0565	0.0538	0.0504

proposed observer and observer in Vasiljevic and Khalil (2008) are similar, where the transient response of the proposed method is improved over the observer in Vasiljevic and Khalil (2008); moreover, both methods have lower frequency content than the observer in Xian et al. (2004) and the central difference method. To illustrate the lower frequency response of the proposed method compared to Xian et al. (2004) and the central difference method, frequency analysis plots of the experiment results are shown in Fig. 2(e)–(l).

Given the lack of velocity sensors in the two-link experiment testbed to verify the velocity estimates, a simulation was performed using the dynamics in (32). To examine the effect of noise, white Gaussian noise with SNR 60 dB is added to the position measurements. Fig. 3 shows the simulation results for the steady-

state velocity estimation errors and the respective frequency analysis for the velocity estimate of the observer in Xian et al. (2004), the observer in Vasiljevic and Khalil (2008), the developed method, and the central difference method. Table 1 gives a comparison of the transient and steady state RMS (Root Mean Square) velocity estimation errors for these different methods. Results of the standard numerical central differentiation algorithm are significantly worse than the other methods in the presence of noise as seen from Fig. 3 and Table 1. Although, simulation results for Vasiljevic and Khalil (2008) and the developed method are comparable, differences exist in the structure of the observers and proof of convergence of the estimates. The observer in Vasiljevic and Khalil (2008) is a purely robust feedback technique and the estimation result is proven to be asymptotic as the gains tend

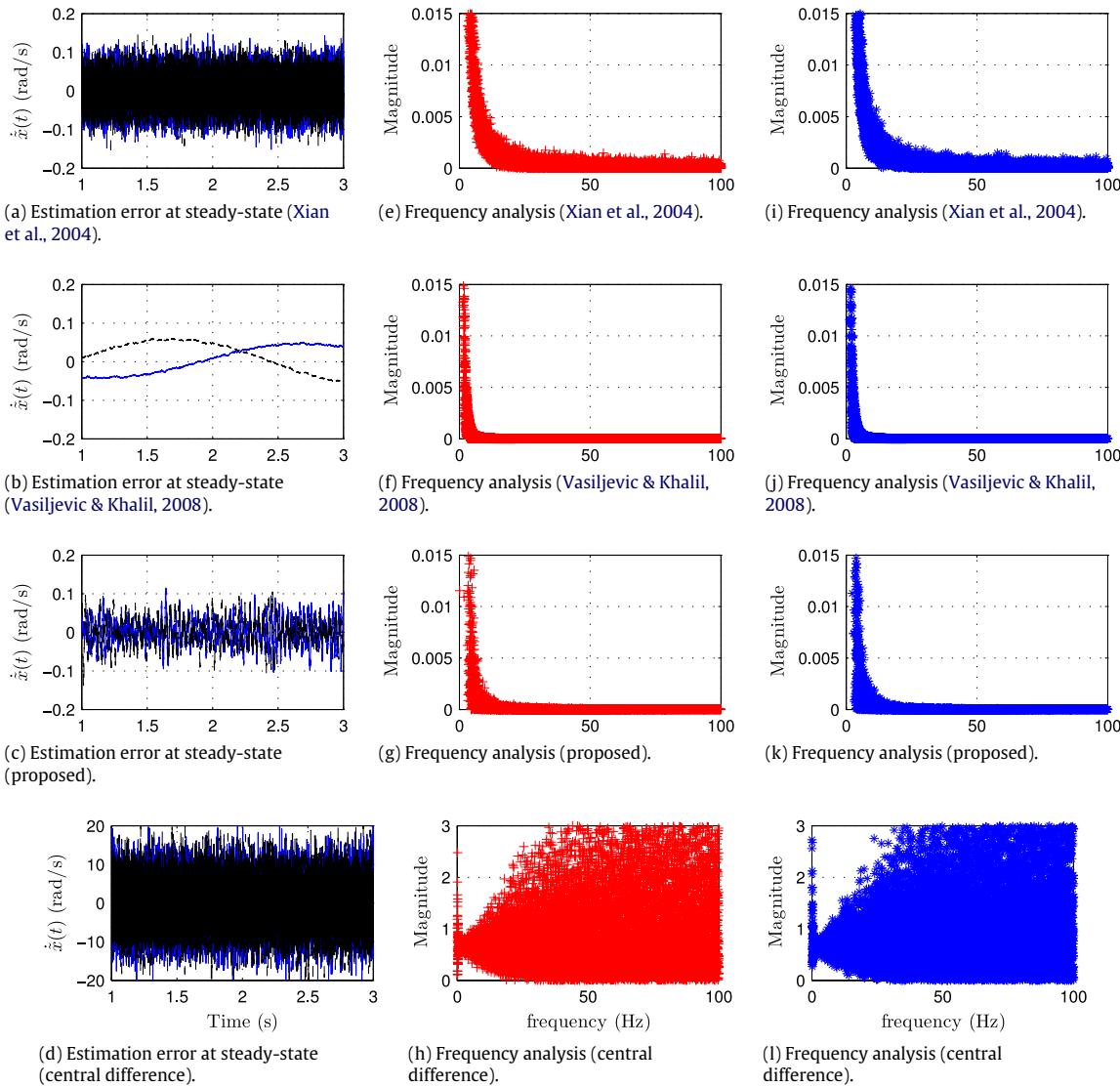


Fig. 3. The steady-state velocity estimation error $\dot{\hat{x}}$ using (a) Xian et al. (2004), (b) Vasiljevic and Khalil (2008), (c) the proposed method, and (d) the center difference method on simulations, in presence of sensor noise (SNR 60 dB) (solid line: Link 1, dashed line: Link 2). The other figures (e)–(l) indicate the respective frequency analysis of velocity estimation $\dot{\hat{x}}$ (plus marker: Link 1, asterisk marker: Link 2).

to infinity. On the other hand, the proposed method is a robust adaptive observer with a DNN structure to learn the system uncertainties, combining a dynamic filter and a robust sliding mode structure, thus guaranteeing asymptotic convergence with finite gains. Further, the observer in Xian et al. (2004) is also a purely robust feedback method, where all uncertainties are damped out by a sliding mode term resulting in higher frequency velocity estimates than the developed observer, as seen from both experiment and simulation results.

5. Conclusion

A novel design of an adaptive observer using DNNs for high-order uncertain nonlinear systems is proposed. The DNN works in conjunction with a dynamic filter without an off-line training phase. A sliding feedback term is added to the DNN structure to account for reconstruction errors and external disturbances. The observation states are proven to asymptotically converge to the system states. Simulations and experiments on a two-link robot manipulator show the improvement of the proposed method in comparison to several other estimation methods.

References

- Adhyaru, D. M. (2012). State observer design for nonlinear systems using neural network. *Applied Soft Computing*, *12*, 2530–2537.
- Astolfi, A., Ortega, R., & Venkatraman, A. (2010). A globally exponentially convergent immersion and invariance speed observer for mechanical systems with non-holonomic constraints. *Automatica*, *46*, 182–189.
- Aubin, J. P., & Frankowska, H. (2008). *Set-valued analysis*. Birkhäuser.
- Bhasin, S., Kamalapurkar, R., Dinh, H. T., & Dixon, W. (2013). Robust identification-based state derivative estimation for nonlinear systems. *IEEE Transactions on Automatic Control*, *58*, 187–192.
- Boulkroune, A., Tadjine, M., Msaad, M., & Farza, M. (2008). How to design a fuzzy adaptive controller based on observers for uncertain affine nonlinear systems. *Fuzzy Sets and Systems*, *159*, 926–948.
- Calise, A. J., Hovakimyan, N., & Idan, M. (2001). Adaptive output feedback control of nonlinear systems using neural networks. *Automatica*, *37*, 1201–1211.
- Canudas De Wit, C., & Slotine, J.-J. (1991). Sliding observers for robot manipulators. *Automatica*, *27*, 859–864.
- Choi, J., & Farrell, J. (1999). Adaptive observer for a class of nonlinear systems using neural networks. In *1999 IEEE international symposium on intelligent control/intelligent systems and semiotics* (pp. 114–119).
- Clarke, F. H. (1990). *Optimization and nonsmooth analysis*. SIAM.
- David, J., Fridman, L., & Levant, A. (2005). Second-order sliding-mode observer for mechanical systems. *IEEE Transactions on Automatic Control*, *50*, 1785–1789.
- Dawson, D., Qu, Z., & Carroll, J. (1992). On the state observation and output feedback problems for nonlinear uncertain dynamic systems. *Systems & Control Letters*, *18*, 217–222.

- Dinh, H., Bhasin, S., & Dixon, W. E. (2010). Dynamic neural network-based robust identification and control of a class of nonlinear systems. In *Proc. IEEE conf. decis. control* (pp. 5536–5541).
- Dinh, H. T., Kamalapurkar, R., Bhasin, S., & Dixon, W. E. (2011). Dynamic neural network-based robust observers for second-order uncertain nonlinear systems. In *Proc. IEEE conf. decis. control* (pp. 7543–7548).
- Dixon, W. E., Behal, A., Dawson, D. M., & Nagarkatti, S. (2003). *Nonlinear control of engineering systems: a Lyapunov-based approach*. Boston: Birkhäuser.
- Filippov, A. (1964). Differential equations with discontinuous right-hand side. *American Mathematical Society Translations*, 42(2), 199–231.
- Filippov, A. F. (1988). *Differential equations with discontinuous right-hand sides*. Kluwer Academic Publishers.
- Fischer, N., Kamalapurkar, R., & Dixon, W. E. (2013). LaSalle-Yoshizawa corollaries for nonsmooth systems. *IEEE Transactions on Automatic Control*, 58, 2333–2338.
- Funahashi, K., & Nakamura, Y. (1993). Approximation of dynamic systems by continuous-time recurrent neural networks. *Neural Networks*, 6, 801–806.
- Hornick, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural Networks*, 4, 251–257.
- Kim, Y. H., & Lewis, F. L. (1999). Neural network output feedback control of robot manipulators. *IEEE Transactions on Robotics and Automation*, 15, 301–309.
- Kim, Y. H., Lewis, F. L., & Abdallah, C. T. (1997). A dynamic recurrent neural-network-based adaptive observer for a class of nonlinear systems. *Automatica*, 33, 1539–1543.
- Krstic, M., Kokotovic, P. V., & Kanellakopoulos, I. (1995). *Nonlinear and adaptive control design*. John Wiley & Sons.
- Lee, K. W., & Khalil, H. K. (1997). Adaptive output feedback control of robot manipulators using high-gain observer. *International Journal of Control*, 67, 869–886.
- Lewis, F. L., Selmic, R., & Campos, J. (2002). *Neuro-fuzzy control of industrial systems with actuator nonlinearities*. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics.
- Lotfi, N., & Namvar, M. (2010). Global adaptive estimation of joint velocities in robotic manipulators. *IET Control Theory and Applications*, 4, 2672–2681.
- Mohamed, M., Karim, T., & Safya, B. (2010). Sliding mode observer for nonlinear mechanical systems subject to nonsmooth impacts. In *Int. multi-conf. syst. signals devices*.
- Paden, B., & Sastry, S. (1987). A calculus for computing Filippov's differential inclusion with application to the variable structure control of robot manipulators. *IEEE Transactions on Circuits and Systems*, 34(1), 73–82.
- Park, J. H., & Park, G.-T. (2003). Adaptive fuzzy observer with minimal dynamic order for uncertain nonlinear systems. *IEE Proceedings—Control Theory and Applications*, 150, 189–197.
- Polycarpou, M., & Ioannou, P. (1991). *Identification and control of nonlinear systems using neural network models: design and stability analysis*. Systems Report 91-09-01. University of Southern California.
- Shevitz, D., & Paden, B. (1994). Lyapunov stability theory of nonsmooth systems. *IEEE Transactions on Automatic Control*, 39(9), 1910–1914.
- Shin, E., & Lee, K. (1999). Robust output feedback control of robot manipulators using high-gain observer. In *IEEE int. conf. on control and appl.*.
- Slotine, J.-J., Hedrick, J., & Misawa, E. A. (1986). On sliding observers for nonlinear systems. In *Proc. Am. control conf.* (pp. 1794–1800).
- Smirnov, G. V. (2002). *Introduction to the theory of differential inclusions*. American Mathematical Society.
- Vargas, J., & Hemerly, E. (2001). Adaptive observers for unknown general nonlinear systems. *IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics*, 31, 683–690.
- Vasiljevic, L., & Khalil, H. (2008). Error bounds in differentiation of noisy signals by high-gain observers. *Systems & Control Letters*, 57, 856–862.
- Xian, B., de Queiroz, M. S., Dawson, D. M., & McIntyre, M. (2004). A discontinuous output feedback controller and velocity observer for nonlinear mechanical systems. *Automatica*, 40, 695–700.