

Tao XUE, Zi-wei WANG, Tao ZHANG, Ou BAI, Meng ZHANG, Bin HAN, 2020.
Fixed-time constrained acceleration reconstruction scheme for robotic
exoskeleton via neural networks. *Frontiers of Information Technology &
Electronic Engineering*, 21(5):705-722. <https://doi.org/10.1631/FITEE.1900418>

Fixed-time constrained acceleration reconstruction scheme for robotic exoskeleton via neural networks

Key words: Acceleration reconstruction; Fixed-time convergence;
Constrained control; Barrier Lyapunov function; Initial state
irrelevant technique; Robotic exoskeleton

Corresponding author: Tao ZHANG

E-mail: taozhang@tsinghua.edu.cn

 ORCID: <https://orcid.org/0000-0002-2980-6281>

Motivation

1. Acceleration is extremely essential in dynamical modeling, assistance planning, and motion intention estimation of exoskeleton systems.
2. Acceleration cannot be directly measured by existing commonly used sensors. Moreover, due to the complex interaction disturbances and fast-changing acceleration signals, accurate acceleration estimation remains challenging.
3. The performances of existing acceleration reconstruction schemes depend on the initial states, and the reconstruction errors are not constrained, which seriously limit the practical applications of the acceleration observer.
4. To the best knowledge of the authors, initial-state-irrelevant and observation-error-constrained techniques have not been well explored for acceleration observation.

Main idea

1. The acceleration reconstruction error can be constrained with the barrier Lyapunov function.
2. The predefined convergence time that is independent of disturbances and the initial states can be obtained via a fixed-time control technique.
3. To eliminate the complex human-exoskeleton interaction disturbances, a radial basis function neural network is used to learn the model parameters and approximate the disturbances.

Method

1. We present a new exponential-type barrier Lyapunov function (EBLF) to address the error constraint issue, and reveal the equivalence between EBLF and the commonly used quadratic function when there are no constraints. Different from the log-type barrier Lyapunov function, EBLF is a more general Lyapunov function that can also be applied in a non-constrained system.

$$\Psi(l, z) = l^2 \left(\exp \frac{z^T z}{l^2 - z^T z} - 1 \right)$$

$$\Psi(l, z) \geq l^2 \frac{z^T z}{l^2 - z^T z} \geq 0$$

$$\lim_{\|z\| \rightarrow l} \Psi(l, z) = +\infty$$

$$\lim_{l \rightarrow \infty} \Psi(l, z) = z^T z$$

Method

2. To obtain fixed-time convergence, fractional power sliding model control is designed to guarantee the initial state and disturbance-irrelevant convergence.

$$\left\{ \begin{array}{l} \dot{\hat{x}}_1 = \hat{x}_2 + T\hat{x}_1 - K_1\tilde{x}_1 - v_1, \\ \dot{\hat{x}}_2 = -H^{-1}(\dot{H} + C)\hat{q} - H^{-1}\dot{C}\dot{q} \\ \quad - H^{-1}(\dot{G} - \dot{\tau}) + H^{-1}\delta(\dot{q}, \hat{q}) - T^2\hat{x}_1 \\ \quad - T\hat{x}_2 - K_2\tilde{x}_1 - v_2 - \alpha_4\text{sign}(\tilde{x}_1), \\ \text{sig}(\xi)^\alpha = \left[|\xi_1|^\alpha \text{sign}(\xi_1), |\xi_2|^\alpha \text{sign}(\xi_2), \dots, \right. \\ \quad \left. |\xi_n|^\alpha \text{sign}(\xi_n) \right], \\ \xi = [\xi_1, \xi_2, \dots, \xi_n]^T, \end{array} \right.$$

Method

3. To enhance the control performance, a radial basis function neural network (RBFNN) with an adaptive weight matrix law is proposed to approximate and attenuate most disturbances, and the remaining perturbation is left to the sliding mode control law to suppress .

$$f(X) = (W^*)^T \varphi(X) + \epsilon^*, \quad \|\epsilon^*\| \leq \epsilon_N,$$

$$\begin{cases} \widehat{W} = \frac{l_b^2}{l_b^2 - R_1^2} e^{\frac{R_1^2}{l_b^2 - R_1^2}} (\eta \varphi(\dot{q}, \hat{q}) \dot{q}^T - \eta \pi), \\ \dot{\pi} = \frac{d\varphi(\dot{q}, \hat{q})}{dt} \dot{q}^T + \varphi(\dot{q}, \hat{q}) (\hat{x}_2 + T \dot{q})^T, \end{cases}$$

Method

4. Based on EBLF, the fractional power sliding control law, and the RBFNN disturbance observer, an acceleration reconstruction scheme is developed, in which the convergence time is irrelevant to the initial states or disturbance, but dependent on the chosen parameters, and the observation errors are strictly limited within the prescribed error bounds.

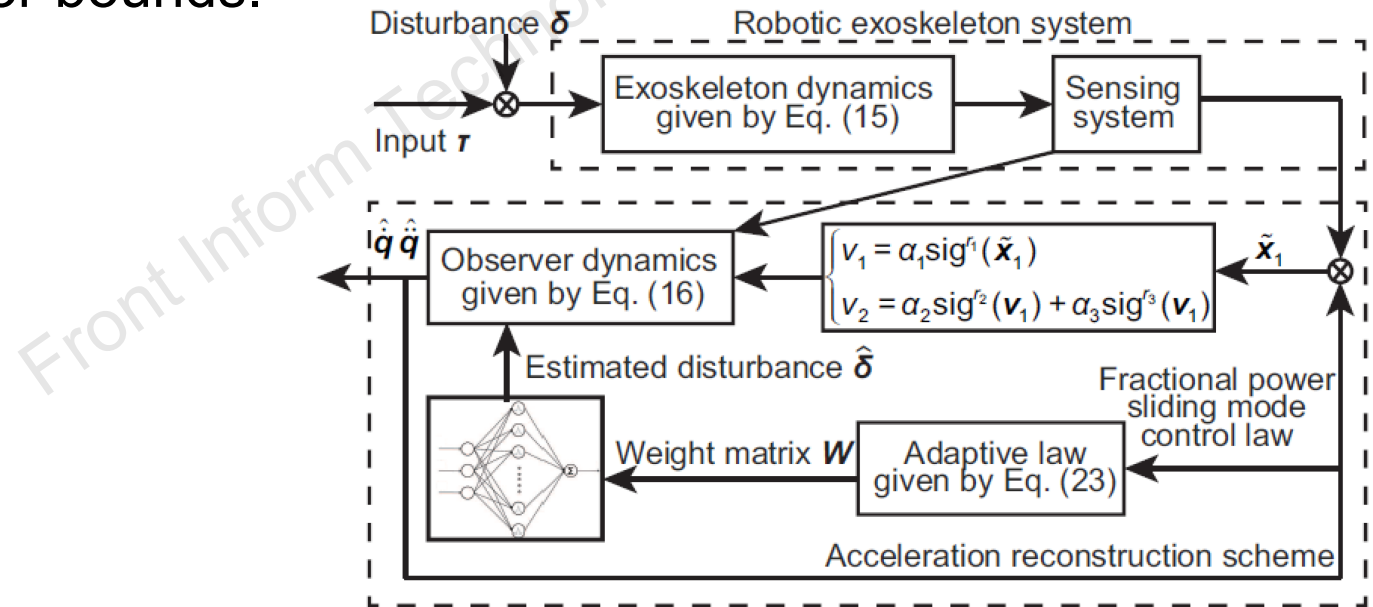


Fig. 2 Schematic of the proposed fixed-time acceleration reconstruction scheme

Major results

Simulation on the 2-link model

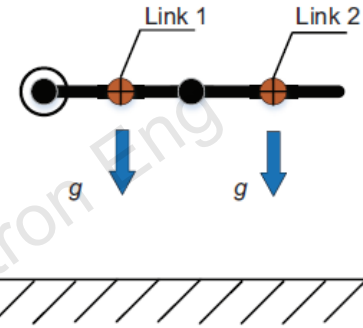


Fig. 3 Schematic diagram of the simulation environment

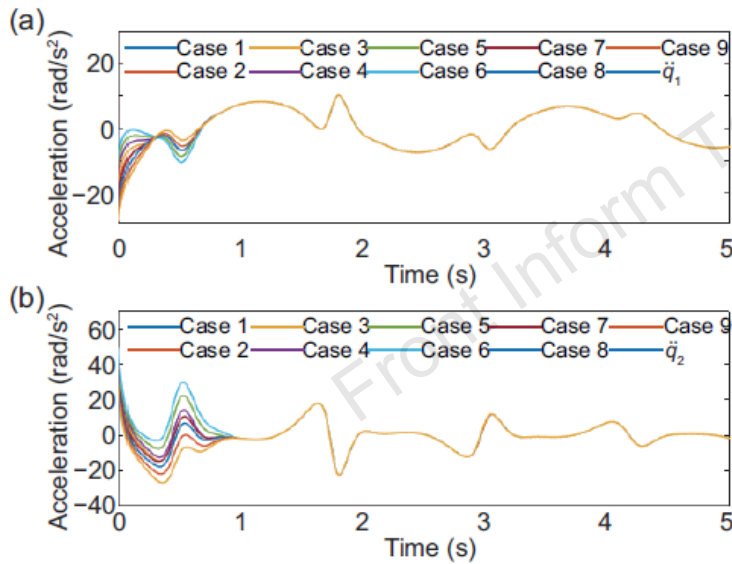


Fig. 5 Trajectories of observed and actual accelerations: (a) observed acceleration \hat{q}_1 and actual acceleration \ddot{q}_1 ; (b) observed acceleration \hat{q}_2 and actual acceleration \ddot{q}_2

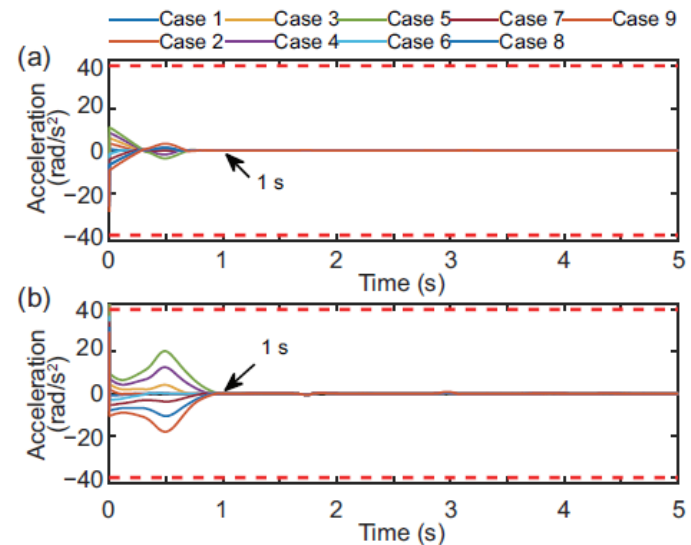


Fig. 7 Acceleration observation errors of \hat{q}_1 (a) and \hat{q}_2 (b)

Major results

Walking experiments with exoskeleton assistance



Fig. 10 Walking assistance with robotic exoskeleton

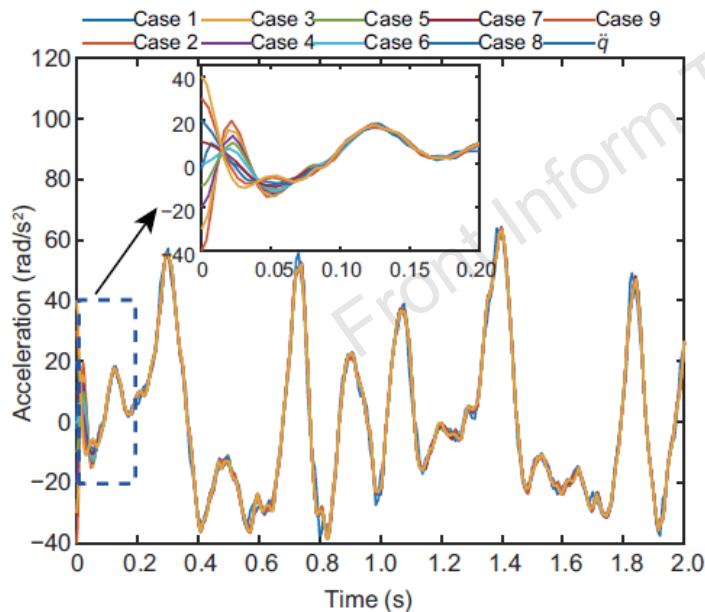


Fig. 13 Acceleration tracking performance via the proposed scheme in the walking experiments

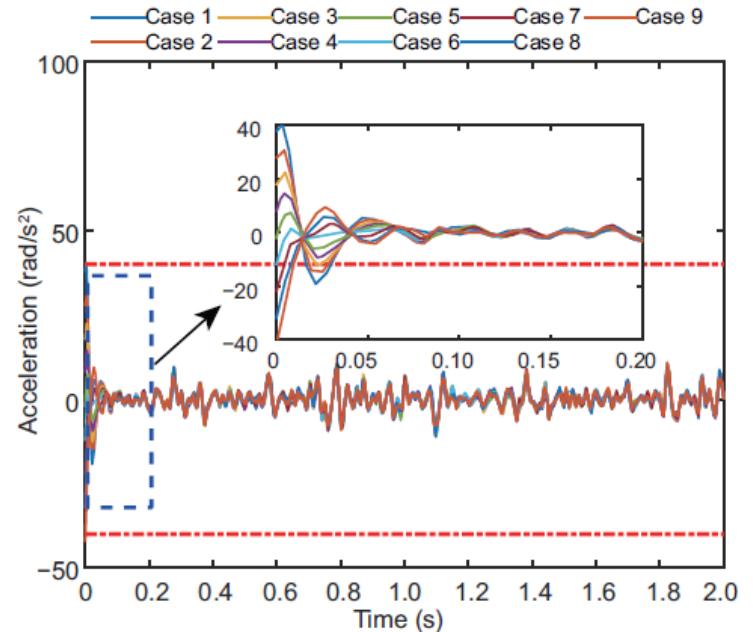


Fig. 14 Acceleration reconstruction errors via the proposed scheme in the walking experiments

Major results

Sit-to-stand experiments with exoskeleton assistance



Fig. 17 A sit-to-stand cycle with exoskeleton assistance

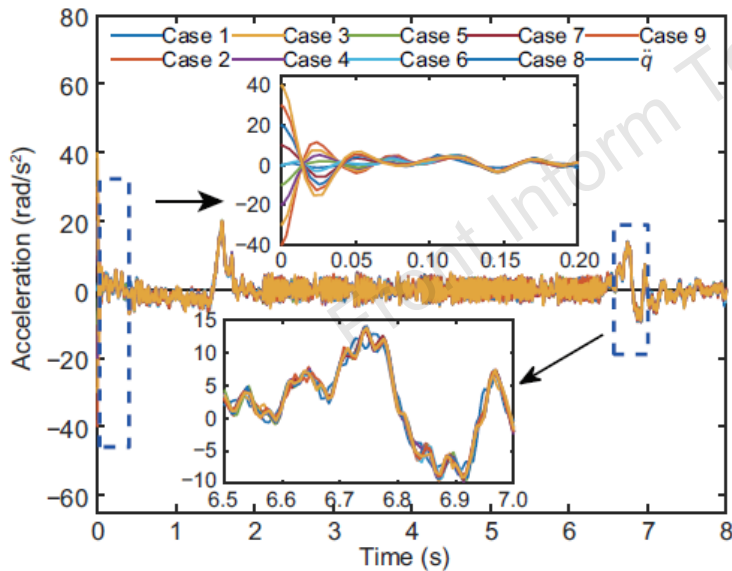


Fig. 20 Acceleration tracking performance via the proposed scheme in the sit-to-stand experiments

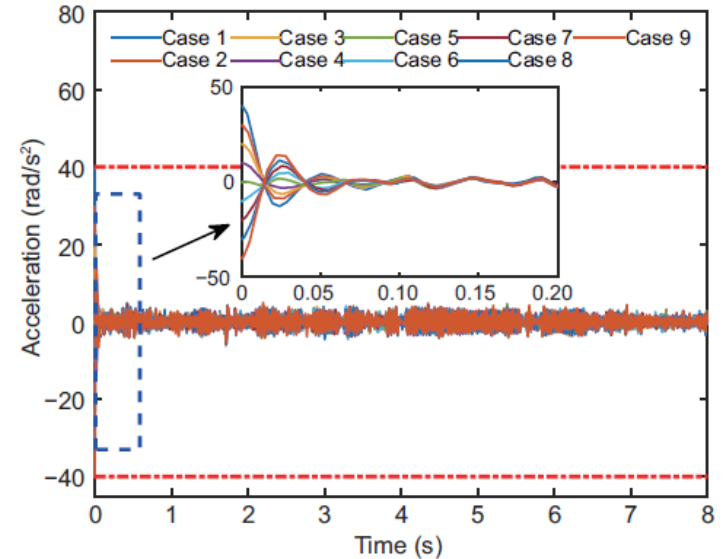


Fig. 21 Acceleration reconstruction errors via the proposed scheme in the sit-to-stand experiments

Conclusions

1. Both the simulation and physical experiments validate the unique properties of the proposed algorithm, i.e., fixed-time convergence, initial state irrelevance, high reconstruction accuracy, perfect disturbance suppression, and excellent static-dynamic performance.
2. Compared with the linear differential observer, the estimation performance is strongly improved in dynamic motions like walking and is also enhanced in static motions like squatting, which account for most of the activities of daily living.

Table 4 Performance comparison

Scenario	RMSE (rad/s ²)			Maximum error (rad/s ²)		
	Proposed scheme	Linear observer	Reduction	Proposed scheme	Linear observer	Reduction
Walking	3.15	18.85	82.29%	10.55	51.53	79.52%
Squatting	1.76	2.00	12.08%	4.31	9.98	56.75%



Tao XUE received the BS degree in the Department of Automation from Northeastern University, Shenyang, China, in 2012. He is currently a PhD student in the Department of Automation, Tsinghua University, Beijing, China. His research interests include robotic exoskeleton, adaptive control, and compliant control.



Zi-wei WANG received his BS degree in Department of Control Science and Technology from Harbin Institute of Technology, Harbin, China, in 2012. He is currently pursuing a PhD degree in Guidance and Control Institute, Department of Automation, Tsinghua University, Beijing, China. His current research interests include teleoperation control, robotics, and control systems.



Tao ZHANG received the PhD degree in control science and engineering from Tsinghua University, Beijing, China, in 1999 and the PhD degree in electrical engineering from Saga University, Saga, Japan, in 2002.

He became an associate professor at Saga University in 2002 and a research scientist in the National Institute of Informatics, Tokyo, Japan, in 2003. In 2006, he became an associate professor at the Department of Automation, Tsinghua University. His current research interests include pattern recognition, nonlinear system control, robotics, control engineering, and artificial intelligent.

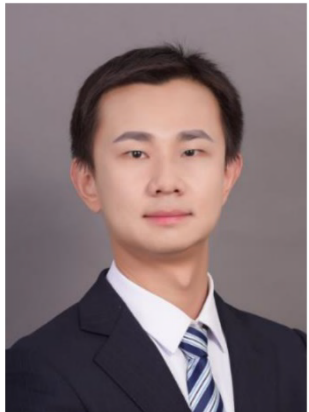


Ou BAI received the BS degree in electronic engineering from Tsinghua University, China, and the PhD degree in advanced systems control engineering from Saga University, Japan. Dr. BAI finished the post-doctoral research training in the National Institutes of Health. Dr. BAI currently serves as the Director of Human Cyber-Physical Systems Laboratory and is an associate professor in the Department of Electrical and Computer Engineering, Florida International University. Dr. BAI has published 100 peer-reviewed journal papers, book chapters, and conference proceeding papers. Dr. BAI's research is highly interdisciplinary with collaborations from academia, industry, medical institutes, and government laboratories.



Meng ZHANG received the MS degree in biomedical engineering from State University of New York at Stony Brook, USA, after obtaining the BS degree in engineering mechanics from Tsinghua University. He founded Move Robotics Technology Co., Ltd., in late 2017 after 5 years at Rethink Robotics, Inc., where he helped bring Baxter and Sawyer, world's first collaborative robots, from lab to life.

His current work is focused on adding advanced control technology and artificial intelligence at the intersection of robotics and medical world, making robots that are suitable for everyone.



Bin HAN received the BS and PhD degrees in mechanical engineering and mechatronics from Huazhong University of Science and Technology (HUST), Wuhan, China, in 2008 and 2013, respectively. From 2014 to 2016, he joined the Department of Automation in Tsinghua University as a Postdoctoral Fellow.

He is currently a lecturer of the State Key Laboratory of Digital Manufacturing Equipment and Technology, HUST. His research interests include biomimetic robots, legged robots, dynamic balance control, and exoskeleton. Dr. HAN is a member of the IEEE Robotics and Automation Society.