CPS: Small: Real-Time Machine Learning-based Control of Human Cyber-Physical Balance Systems

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• Human Cyber-Physical Balance Systems (HCPBS)

Figure 1: A set of example of human cyber-physical balance systems, such as Furuta pendulum, autonomous bikebot and bipedal walkers (from left to right).

Control Goal and Challenges

- ❑ **Goal**: Achieve trajectory tracking and balance tasks with fewer numbers of control inputs than degrees of freedom
- ❑ **Challenges**: Trajectory tracking and balance tasks are intertwined and no analytical casual controller to achieve exactly tracking

Research project objective: Develop a real-time machine learning-based control framework for human cyber-physical balance systems (HCPBS)

• Overview Design of the Learning-based Control of HCPBS

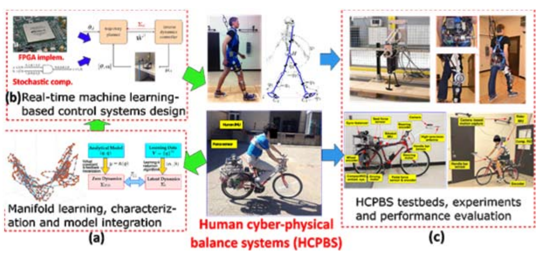

Figure 2: Concepts of the real-time machine learning-based control of HCPBS.

Basic System Components

- ❑ A machine learning-based modeling and characterization
- ❑ Hardware co-design real-time learning-based robust control
- ❑ Multiple robotic testbeds testing, validation and performance evaluation

• Learning-based Robust Control Design

- The HCPBS dynamics are captured by an external (actuated) and an internal (unactuated) subsystems
- Problem statement: $\theta(t) \to \theta_d(t)$ (given) and $\alpha(t) \to \alpha_d(\theta, \theta_d)$ (unknown)

$$\begin{cases} \Sigma_e : \dot{\theta}_1 = \theta_2,\ \dot{\theta}_2 = f_\theta(\theta, \alpha, u), \\ \Sigma_i : \dot{\alpha}_1 = \alpha_2,\ \dot{\alpha}_2 = f_\alpha(\theta, \alpha, u). \end{cases} \xrightarrow[u_d \sim v + gp_\alpha]{v = f_\alpha(\theta,\alpha,u)} \begin{cases} \Sigma_e : \dot{\theta}_1 = \theta_2,\ \dot{\theta}_2 \sim gp_\theta, \\ \Sigma_i : \dot{\alpha}_1 = \alpha_2,\ u_d - \dot{\alpha}_2 \sim gp_\alpha. \end{cases}$$

- Gaussian process is used to estimate the external and internal subsystems dynamics

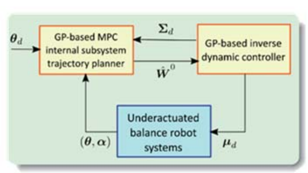

Figure 3: Schematic of the learning-based control design.

• Learning-based Control Properties

- The external subsystem tracking and internal subsystem balance errors are proven to be bounded
- The predictive GP covariance is integrated with the MPC design to improve control robustness
- No balanced training data is needed and it is attractive for field testing

• Scientific Impacts

- The proposed learning-based control of HCPBS will generate algorithms and enabling tools for control design for complex human-in-the-loop CPS
- The characterization of physical principle-based dynamic models and data-driven models enables a new control design for many human CPS applications
- The integration of data-driven model and learning-based control provides new perspectives on performance enhancement of safety-critical or mission-critical CPS in dynamic, uncertain environments
- The development of hardware/software co-design accelerator brings new real-time machine learning schemes that enable the computationally intensive control systems in many CPS applications

• Hardware Architecture Design for Matrix Inversion-based GP Models

- Explored efficient hardware architecture for GP implementation, including covariance generation, matrix inversion and post-processing modules
- The proposed hardware accelerator achieves 2991× and 1857× less area and power consumption, respectively (compared to Intel Core i7-7700K CPU)

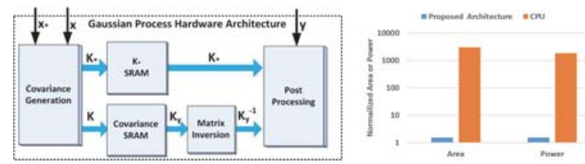

Figure 4: (a) An overview architecture of GP implementation. (b) Performance comparison with the CPU implementation.

• Experimental Testbed and Validation

- Build autonomous bikebot testbed platform
- Implemented both the external/internal convertible (EIC)-based control (i.e., physical model-based) and the GP-based learning control
- Compared the results under the two controller

Figure 5: Experimental testbed for autonomous bikebot.

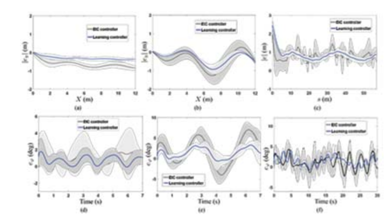

Figure 6: Mean error profiles with variance for (a) straight-line, (b) sinusoidal, and (c) circular trajectories and roll angle errors (d)-(f) for these trajectories.

• Broader Impacts

- The experiments demonstrated that the learning-based control outperformed the physical-model control with 50% tracking error reduction
- Supported and trained four graduate students (three PhD and one MS level) and three undergraduate students
- Presented two conference papers and two journal publications in the past year

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