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).

Research Goal and Challenges

- ❑ **Goal**: Develop a real-time machine learning-based control framework for human cyber-physical balance systems (HCPBS)
- ❑ **Challenges**: Trajectory tracking and balance tasks are intertwined and no analytical casual controller to achieve exactly tracking

• Overview Design of Learning-based Control of HCPBS

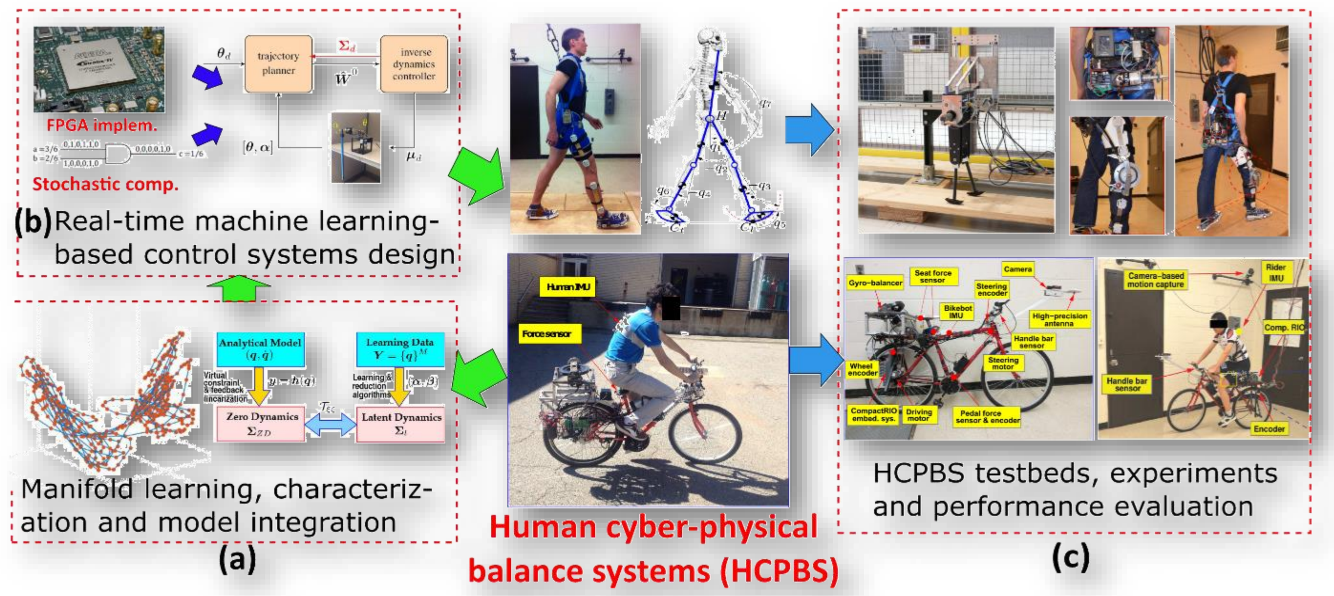

Figure 2: Concepts of the real-time machine learning-based control of HCPBS.

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

• Machine Learning-enabled Human Walker Activity and Pose Estimation

- Real-time human walker activity and pose estimation by only one wearable inertial measurement unit (IMU)
- Long short-term memory (LSTM) models for different activities and gait phase estimation
- Floor slope and human turning angles are considered
- Mapping between the embedded motion manifolds and human joint angles for real-time pose estimation

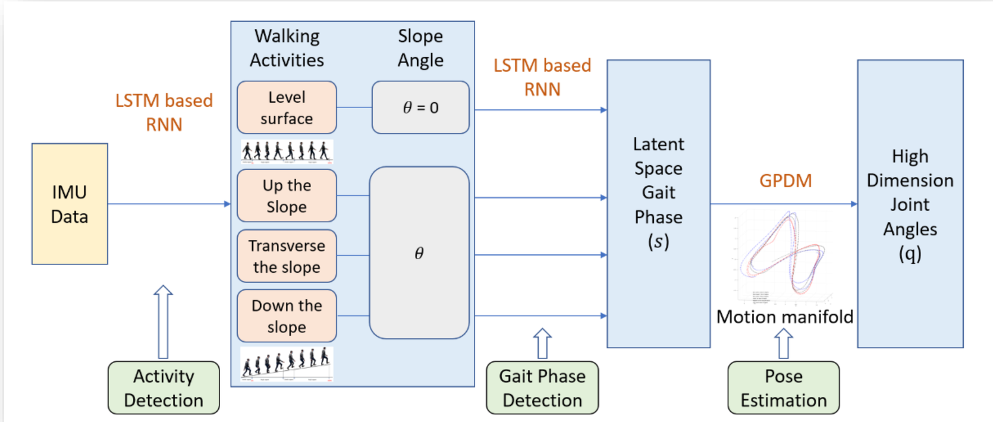

Figure 3: Schematic of the multi-layer learning-enabled, wearable sensor-based activity and pose estimation.

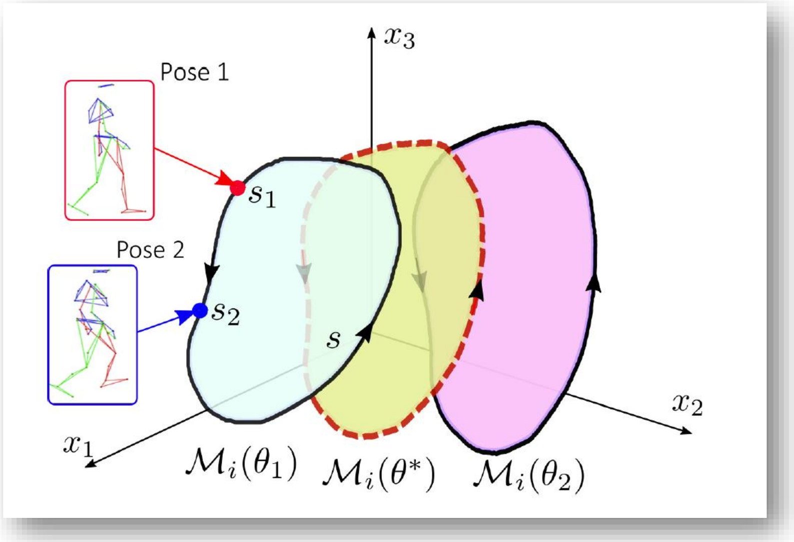

Figure 4: GPDM for pose estimation for various activities and slope angles

- Gaussian Process Dynamic Models (GPDM) is used to map human joint angles $\boldsymbol{y} \in \mathbb{R}^D$ to latent state variable $\boldsymbol{x} \in \mathbb{R}^d$, where $d \ll D$. For activity a_i, $i = 1, \cdots, N$, and slope angle θ, the GPDM is given as

$$\mathcal{M}_i(\theta): \begin{cases} \dfrac{d\boldsymbol{x}_i}{ds} = \boldsymbol{f}_i(\boldsymbol{x}_i, \boldsymbol{\alpha}_i, \boldsymbol{u}_i) + \boldsymbol{\omega}_{pi} \\ \boldsymbol{y}_i = \boldsymbol{g}_i(\boldsymbol{x}_i, \boldsymbol{\beta}_i, \boldsymbol{u}_i) + \boldsymbol{\omega}_{oi} \end{cases}$$

where $\boldsymbol{u}_i$, s and $\boldsymbol{\omega}$ are IMU measurements, gait variable and model noises, respectively. $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$ are GP parameters (obtained by the learning process)

• Learning-based Robust Control Design

- The robot dynamics are captured by an external (actuated) and an internal (unactuated) subsystems
- Problem statement: $\boldsymbol{\theta}(t) \to \boldsymbol{\theta}_d(t)$ (given) and $\boldsymbol{\alpha}(t) \to \boldsymbol{\alpha}_d(\boldsymbol{\theta}, \boldsymbol{\theta}_d)$ (unknown)

$$\begin{cases} \Sigma_e : \dot{\boldsymbol{\theta}}_1 = \boldsymbol{\theta}_2,\ \dot{\boldsymbol{\theta}}_2 = \boldsymbol{f}_\theta(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{u}), \\ \Sigma_i : \dot{\boldsymbol{\alpha}}_1 = \boldsymbol{\alpha}_2,\ \dot{\boldsymbol{\alpha}}_2 = \boldsymbol{f}_\alpha(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{u}). \end{cases} \xrightarrow[\boldsymbol{u}_d \sim \boldsymbol{v} + \boldsymbol{gp}_\alpha]{\boldsymbol{v} = \boldsymbol{f}_\alpha(\boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{u})} \begin{cases} \Sigma_e : \dot{\boldsymbol{\theta}}_1 = \boldsymbol{\theta}_2,\ \dot{\boldsymbol{\theta}}_2 \sim \boldsymbol{gp}_\theta, \\ \Sigma_i : \dot{\boldsymbol{\alpha}}_1 = \boldsymbol{\alpha}_2,\ \boldsymbol{u}_d - \dot{\boldsymbol{\alpha}}_2 \sim \boldsymbol{gp}_\alpha. \end{cases}$$

- Gaussian process (GP) is used to estimate the external and internal subsystems dynamics
  - 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
  - Experimentally validated and demonstrated in rotary pendulum and autonomous bikebot testbed

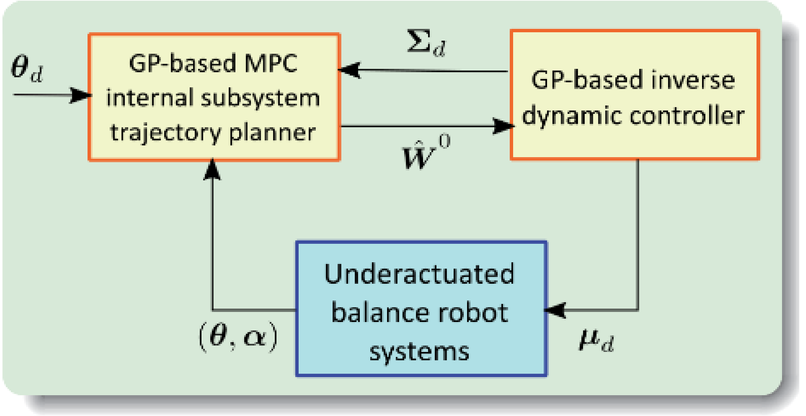

Figure 5: Schematic of the learning-based control design.

• Autonomous Bikebot with Mobile Manipulation and Assistive Leg

- Implemented the external/internal convertible (EIC)-based control (i.e., physical model-based) and the GP-based learning control
- Two extensions were developed for the bikebot with: (1) a 5-DOF onboard manipulator, and (2) two 3-DOF assistive legs
- Developed and tested learning-enhanced control of the mobile manipulation and balance control with assistive leg impulsive actuation

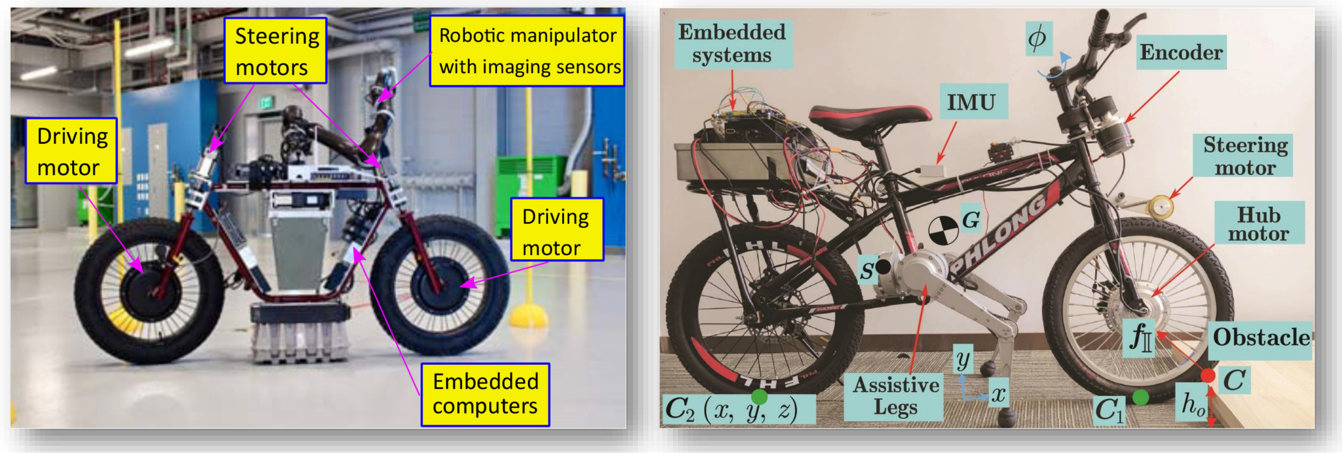

Figure 6 (a) An autonomous bikebot with onboard 5-DOF manipulator (b) An autonomous bikebot with two 3-DOF assistive legs.

• 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 CPS applications

• Broader Impacts

- Demonstrated 50% tracking error reduction by the learning-based control method (vs. physical-model control)
- Learning-enhanced, wearable sensor-based design achieved 93% accuracy for activity detection, 5.7 degs error for 12 limb joint angles, 1.4 degs error for slope angle, and around 30 msec latency for human walking
- Supported and trained six graduate students (five PhD and one MS level) and four undergraduate students (e.g., Rutgers SUPER and LSAMP programs)
- Presented ten conference papers and seven journal publications in the past three years