Jiaqi WANG, Yongzhuo GAO, Dongmei WU, Wei DONG, 2023. Probabilistic movement primitive based motion learning for a lower limb exoskeleton with black-box optimization. *Frontiers of Information Technology & Electronic Engineering*, 24(1):104-116. https://doi.org/10.1631/FITEE.2200065

Probabilistic movement primitive based motion learning for a lower limb exoskeleton with black-box optimization

Key words: Lower limb exoskeleton; Human-robot interaction; Motion learning; Trajectory generation; Movement primitive; Black-box optimization

Corresponding author: Wei DONG
E-mail: dongwei@hit.edu.cn
ORCID: https://orcid.org/0000-0002-1211-6444

Motivation

- When an exoskeleton is used to facilitate the wearer’s movement, a motion generation process often plays an important role in high-level control.

- One of the main challenges in this area is to generate in real time a reference trajectory that is parallel with human intention and can adapt to different situations.

Method description

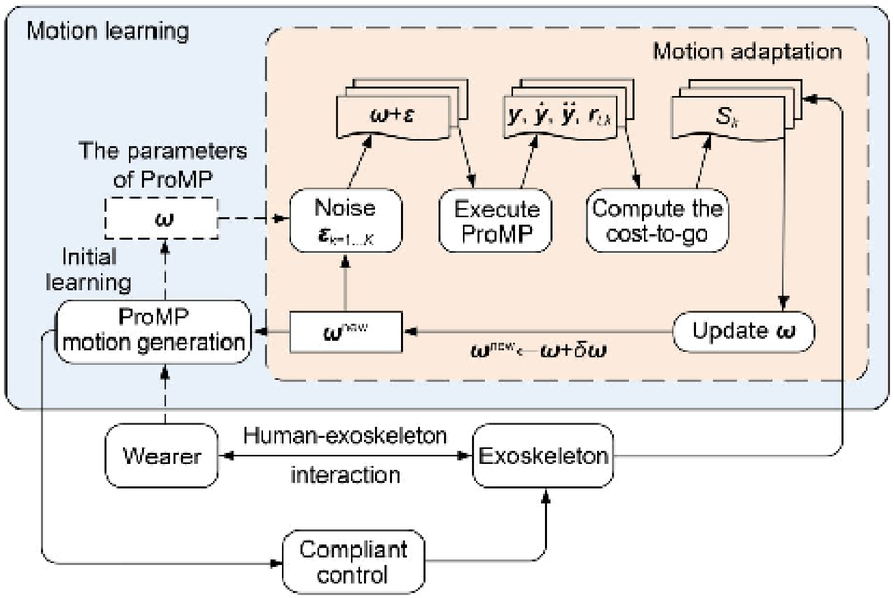


Fig. 1 The working framework of the exoskeleton system with the proposed motion learning strategy

- Motion model generation
  - Step 1: Probabilistic movement primitive (ProMP) algorithm is used to model motion trajectory from demonstrations
  - Step 2: Update online by an optimization algorithm when the subject begin to move
    - PI^{BB} algorithm is used to calculate cost value via actual joint trajectory
    - The parameters of motion model are updated to generate new desired trajectory

Motion representation and initial learning

- Linear basis function to model the joint

$$y_t = \begin{bmatrix} q_t \\ \dot{q}_t \end{bmatrix} = \Phi_t^{\mathrm{T}}(\omega + \varepsilon_t),$$

- Phase function to scale the trajectory

$$z_t = \alpha t.$$

- Basis function representation

$$b_i(z_t) = \exp\left(\frac{\cos(2\pi(z_t - c_i))}{h}\right),$$

- Weights learning result

$$\omega_m = (\Phi^{\mathrm{T}}\Phi + \lambda I)^{-1}\Phi^{\mathrm{T}}Y_m,$$

- Introduce the trajectory distribution

$$p(y_t;\theta) = \int p(y_t|\omega)\,p(\omega;\theta)\,\mathrm{d}\omega.$$

- Take phase function as the variable

$$\phi_t = \phi(z_t).$$

- Trajectory calculation

$$p(y_t;\theta) = \int \mathcal{N}(y_t|\Phi_t^{\mathrm{T}}\omega, \Sigma_y)\,\mathcal{N}(\omega|\mu_\omega, \Sigma_\omega)\,\mathrm{d}\omega = \mathcal{N}(y_t|\Phi_t^{\mathrm{T}}\mu_\omega, \Phi_t\Sigma_\omega\Phi_t^{\mathrm{T}} + \Sigma_y).$$

- Mean and variance

$$\begin{cases} \mu_\omega = \dfrac{1}{M}\sum_{m=1}^{M}\omega_m, \\ \Sigma_\omega = \dfrac{1}{M-1}\sum_{m=1}^{M}(\omega_m - \mu_\omega)(\omega_m - \mu_\omega)^{\mathrm{T}}. \end{cases}$$

Model adaption

- Policy perturbation generated from the trajectory model

$$y_t = \boldsymbol{\Phi}_t^{\mathrm{T}}(\omega + \varepsilon).$$

- Cost function formula

$$M_{t,k} = \frac{J^{-1}\boldsymbol{\Phi}_{t,k}\boldsymbol{\Phi}_{t,k}^{\mathrm{T}}}{\boldsymbol{\Phi}_{t,k}^{\mathrm{T}}J^{-1}\boldsymbol{\Phi}_{t,k}},$$

$$S_k = \sum_{t=0}^{E-1} r_{t,k} + \frac{1}{2}\sum_{t=1}^{E-1}\left(\omega + M_{t,k}\varepsilon_k\right)^{\mathrm{T}},$$

- Immediate cost function

$$r_t = \left(q_t - q_t^{\mathrm{d}}\right)^2,$$

- Overall trajectory cost

$$R = \sqrt{\frac{1}{E}\sum_{t=1}^{E} r_t}.$$

- Probability of the k^{th} roll-out

$$P_k = \mathrm{e}^{-\frac{1}{\gamma}S_k} \Big/ \sum_{k=1}^{K}\mathrm{e}^{-\frac{1}{\gamma}S_k},$$

- Final parameter update

$$\delta\omega = P_k \cdot \varepsilon_k.$$

Algorithm 1 Motion adaptation

Input: initial state of the parameter ω ($\delta\omega$ is weighted averaging), the basis function $\boldsymbol{\Phi}_t$, and desire trajectory y^{d}

Output: parameter vector ω

for $k = 1, 2, \cdots, K$
  Sample $\varepsilon_k \sim \mathcal{N}(0, \Sigma)$
  Roll-out: $y_{t,k} = \boldsymbol{\Phi}_t^{\mathrm{T}}(\omega + \varepsilon_k)$
  $r_{t,k} = \left(q_{t,k} - q_{t,k}^{\mathrm{d}}\right)^2$
  Compute trajectory cost: $M_{t,k} = \frac{J^{-1}\boldsymbol{\Phi}_{t,k}\boldsymbol{\Phi}_{t,k}^{\mathrm{T}}}{\boldsymbol{\Phi}_{t,k}^{\mathrm{T}}J^{-1}\boldsymbol{\Phi}_{t,k}}$
  $S_k = \sum_{t=0}^{E-1} r_{t,k} + \frac{1}{2}\sum_{t=1}^{E-1}\left(\omega + M_{t,k}\varepsilon_k\right)^{\mathrm{T}}$
end for
for $k = 1, 2, \cdots, K$
  Compute the probability of each roll-out:
  $P_k = \mathrm{e}^{-\frac{1}{\gamma}S_k} \Big/ \sum_{k=1}^{K}\mathrm{e}^{-\frac{1}{\gamma}S_k}$
end for
Cost-weighted averaging: $\delta\omega = P_k \cdot \varepsilon_k$
Update: $\omega^{\mathrm{new}} \leftarrow \omega + \delta\omega$
Overall trajectory cost: $R = \sqrt{\frac{1}{E}\sum_{t=1}^{E} r_t}$
until the overall trajectory R cost converges

Experimental protocol

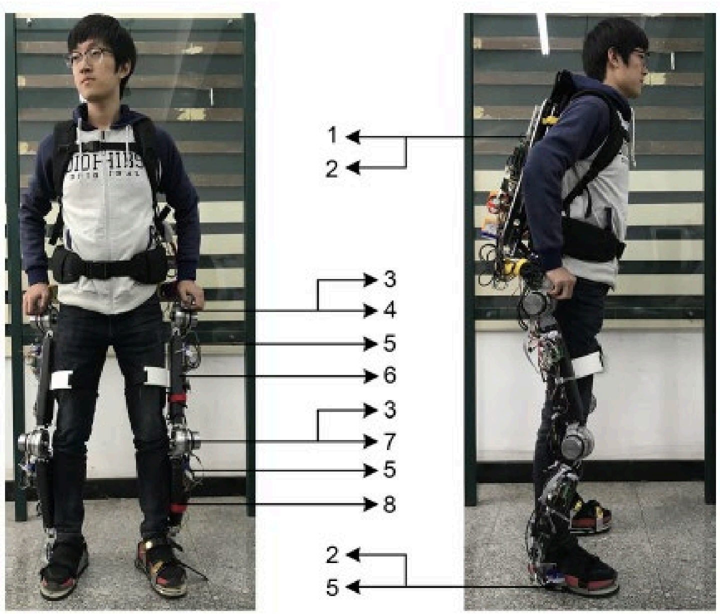


Fig. 6 The hardware system of HEXO exoskeleton
1, backpack; 2, six-axis force sensors; 3, encode and torque sensor; 4, hip joint; 5, inertial measurement unit; 6, thigh limb; 7, knee joint; 8, calf limb

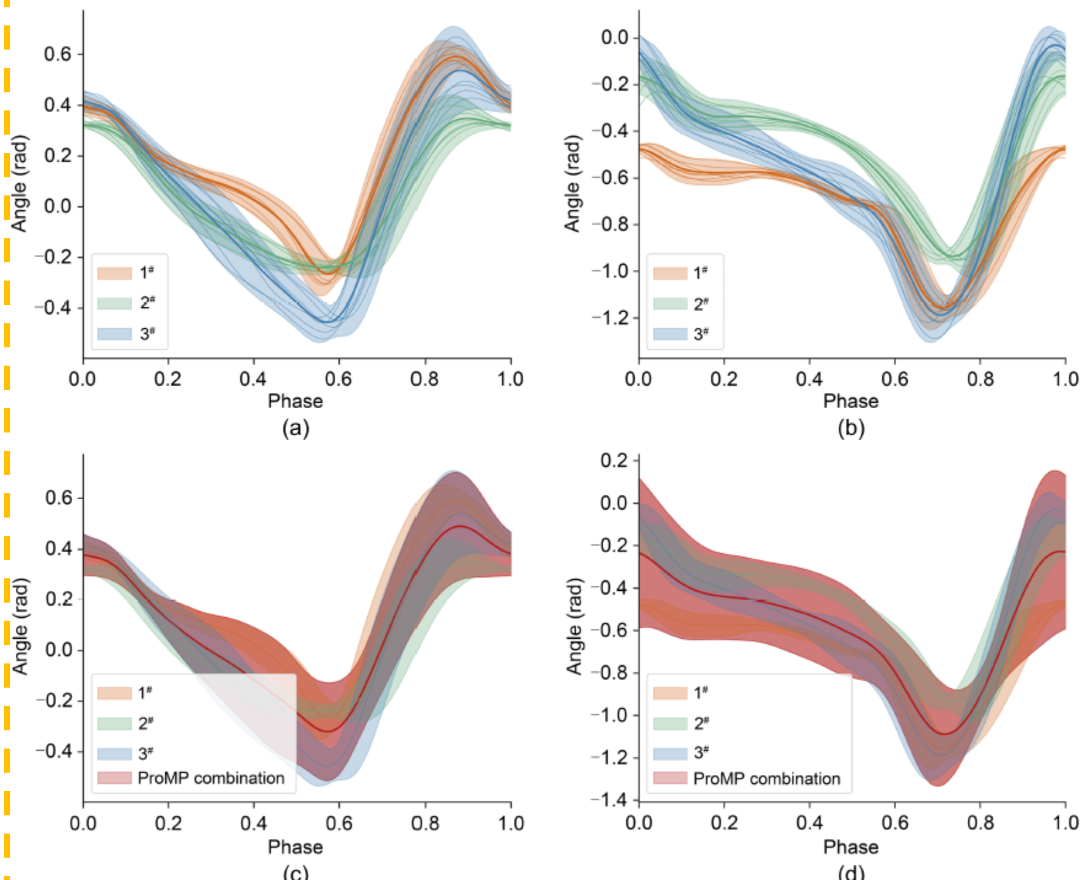
All sensor data were transmitted to the Advanced RISC Machines (ARM) panel through a controller area network (CAN) bus, whose transmission rate was up to 1 Mb/s.

Table 2 Detailed information of the six subjects

Subject index	Gender	Age (year)	Height (cm)	Weight (kg)
1	Male	24	172	66
2	Male	23	180	61
3	Male	24	176	72.5
4	Male	23	187	70
5	Female	24	169	58.5
6	Male	45	179	78

Three voluntary subjects 1, 2, and 3, whose characteristics are listed in Table 2, participated in the data acquisition. Subjects 1, 2, and 3 were asked to perform level walking on a treadmill at their normal speed. The exoskeleton HEXO was working in zero-force mode with no enabled torque assistance, to obtain the most natural gait of the subjects when wearing the exoskeleton.

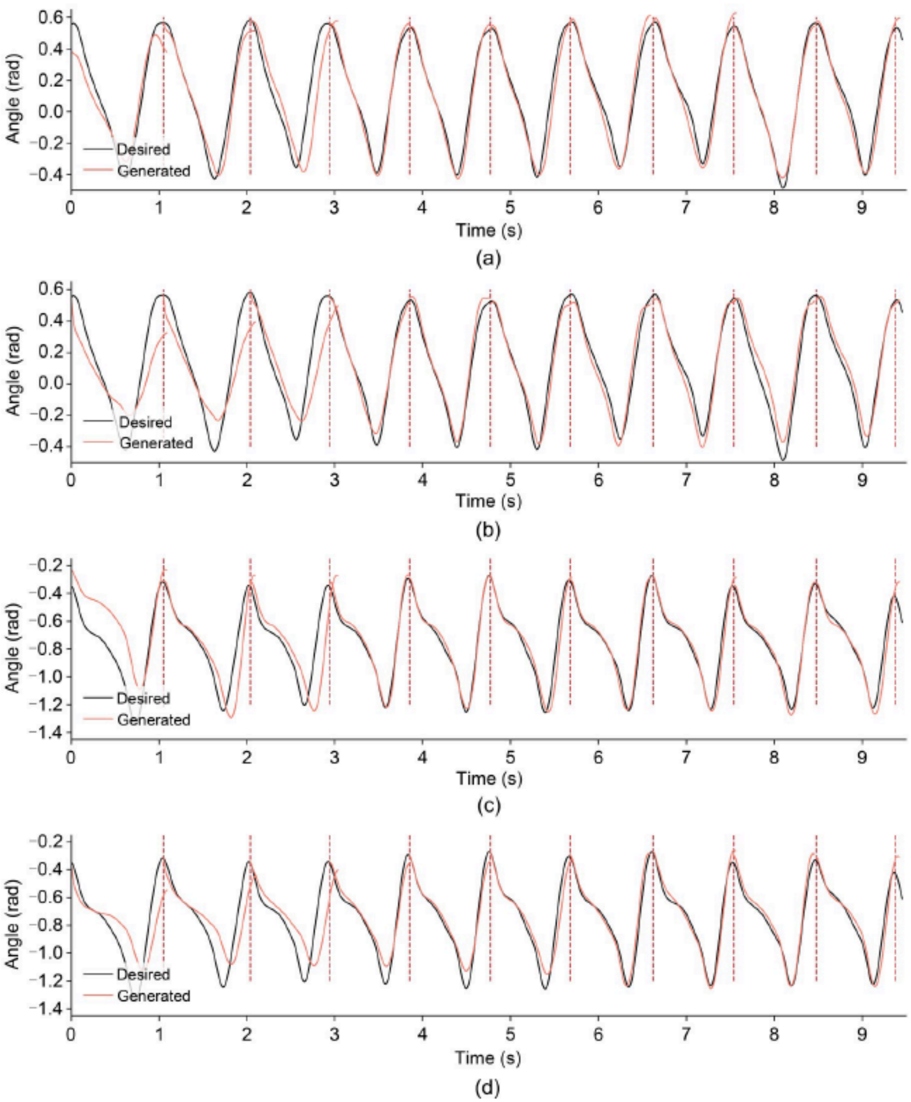
Motion initial learning experiment



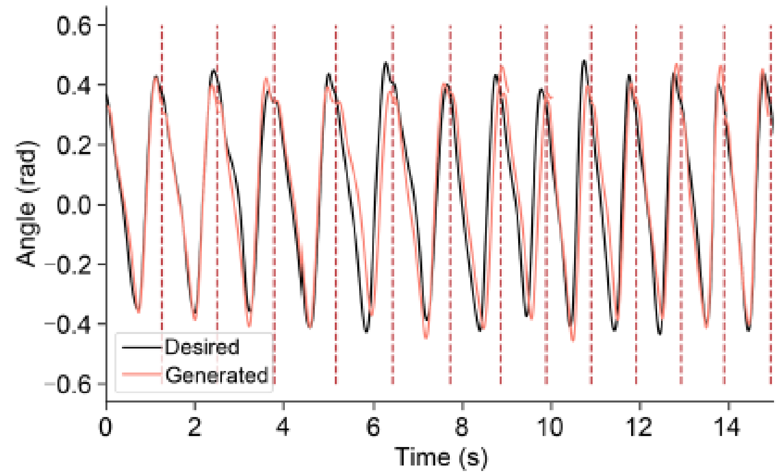
Motion initial learning by ProMP from subjects 1, 2, and 3: (a) mean and covariance of the hip trajectory data; (b) mean and covariance of the knee trajectory data; (c) hip trajectory learned by ProMP; (d) knee trajectory learned by ProMP

Figs. 7a and 7b show the mean and covariance of the hip and knee data, respectively. The general trend of the curve was the same for each joint, but the shape of the curve differed, even when the subjects had relatively similar heights and weights. The red areas of Figs. 7c and 7d show the trajectories learned by ProMP from all three subjects, and contains all the possibilities. The red line can be regarded as the average of all acquired trajectories, so it is more representative than any others. Besides, the more trajectories learned, the more general the reference trajectory.

Motion online adaptation experiment



Motion adaptation process of ProMP-PI^{BB} and DMP-PI^2: (a) hip of ProMP-PI^{BB}; (b) hip of DMP-PI^2; (c) knee of ProMP-PI^{BB}; (d) knee of DMP-PI^2



Trajectory adaptation performance of the proposed ProMP-PI^{BB} when the walking speed changes

In this experiment, there were three new subjects, 4, 5, and 6, as listed in Table 2. To evaluate the effectiveness of the method, subjects with differences were deliberately selected for validation. For example, subject 5 was a female with a lower height and subject 6 was much older than other subjects. The subjects were also asked to deliberately change their speed several times when performing level walking, to test the adaptability of the method to different speeds.

Motion online adaptation experiment

Table 3 The adaptation experiment results (hip/knee) of ProMP-PI^{BB} and DMP-PI^2 for three subjects

Subject index	RMSE (rad)				Convergence step	
	Before adaptation		After adaptation			
	DMP	ProMP	DMP-PI^2	ProMP-PI^{BB}	DMP-PI^2	ProMP-PI^{BB}
4	0.182/0.195	0.101/0.240	0.052/0.040	0.048/0.039	$5^{th}/7^{th}$	$4^{th}/4^{th}$
5	0.301/0.413	0.198/0.288	0.082/0.099	0.065/0.089	$7^{th}/9^{th}$	$3^{rd}/5^{th}$
6	0.087/0.156	0.076/0.123	0.073/0.079	0.057/0.061	$6^{th}/8^{th}$	$3^{rd}/3^{rd}$

Table 3 summarizes the experiment results of the three subjects for DMP-PI^2 and ProMP-PI^{BB}. It shows the RMSEs before adaptation (the first step) and after adaptation, the convergence step, and the improvement rate of the proposed method. Before updating, the RMSEs of ProMP were lower than those of DMP. In the end of the adaptation, the final RMSEs of ProMP-PI^{BB} were also smaller than those of DMP-PI^2. The average improvement for the three subjects was 15.49%, indicating that the proposed strategy achieved better performance. Although the final errors of the two methods were both small, a little mismatch between the desired trajectory and the generated trajectory will cause huge human-robot interaction resistance when the exoskeleton was working. Therefore, any improvement that can reduce the error is valuable.

Conclusions

- In this paper, a novel motion learning scheme to generate a motion trajectory online for lower limb exoskeletons is proposed.
- For motion generation, the motion is modeled by ProMP with offline initial learning using pre-collected trajectories. For motion adaptation, the motion model based on ProMP can be further learned and updated online using the black-box optimization PI^{BB}.
- The exoskeleton with the proposed motion learning is able to adapt to different wearers and variable environments in a timely manner. This human-exoskeleton system can co-work collaboratively faster and more consistently, and with a better human-robot interaction.

Jiaqi WANG received the BS degree from the Harbin Institute of Technology (HIT), in 2017, where she is currently a PhD candidate in the State Key Laboratory of Robotics and Systems. Her current research interest includes robotics, especially wearable exoskeletons, prosthesis, and orthosis.

Yongzhuo GAO received his BS, MS, and PhD degrees in mechanical engineering from the Harbin Institute of Technology. He is currently holding a post-doctoral position with the State Key Laboratory of Robotics and Systems, Harbin Institute of Technology. His research interests include the control strategy and system integration of robotic systems involving industrial robot, medical robot, and compliant manipulators with flexure hinges.

Dongmei WU received the PhD degree in mechatronic engineering from the Harbin Institute of Technology, China, in 2003, where she is currently a Professor. Her research interests include medical robots, robotic system integration, and simulation technology.

Wei DONG received the BS degree in mechanical engineering and the MS and PhD degrees in mechatronics engineering from the Harbin Institute of Technology (HIT), in 2001, 2003, and 2007, respectively. He was a Post-doctoral Researcher with the University of Connecticut, USA, from 2007 to 2009, and CNRS FEMTO-ST, France, from 2009 to 2010. He has extensive experience in a series of inter-related research subjects, including innovative design of robot/mechatronics systems, robotic system modeling and optimization, and smart material and structure integration and their application. He is currently with the State Key Laboratory of Robotics and Systems, HIT. His research interests include the general areas of robotics and mechatronics.