



Adaptive Gait Planning for Walking Assistance Lower Limb Exoskeletons in Slope Scenarios

Chaobin Zou, Rui Huang, *Member, IEEE*, Hong Cheng*, *Senior member, IEEE*, Qiming Chen, Jing Qiu University of Electronic Science and Technology of China (UESTC)

Email: <u>chaubyZou@163.com</u>, <u>hcheng@uestc.edu.cn</u>

Abstract

Lower-limb exoskeletons have gained considerable interests in walking assistance applications for paraplegic patients. In walking assistance of paraplegic patients, the exoskeleton should have the ability to help patients to walk over different terrains in the daily life, such as slope terrains. One critical issue is how to plan the stepping locations on slopes with different gradients, and generate stable and human-like gaits for patients. We proposed an adaptive gait planning approach which can generate gait trajectories adapt to slopes with different gradients for lower-limb walking assistance exoskeletons. We modeled the human-exoskeleton system as a 2D Linear Inverted Pendulum Model (2D-LIPM) with an external force in the two-dimensional sagittal plane, and proposed a Dynamic Gait Generator (DGG) based on an extension of the conventional Capture Point (CP) theory and Dynamic Movement Primitives (DMPs). The proposed approach can dynamically generate reference foot locations for each step on slopes, and human-like adaptive gait trajectories can be reproduced after learning from demonstrated trajectories that sampled from normal healthy human.

Simulation Results

We built a simplified human-exoskeleton simulation model for human-exoskeleton system on the Gazebo simulation platform. The simulation model comprises a torso and two legs, which is restricted to move in the two-dimensional sagittal plane with the active hip joint, active knee joint and passive ankle joint of each leg. During walking simulations, an external force exerted to the model by simulation program through the interface provided by Gazebo simulation platform, which changed over time to estimate the external force exerted by crutches.



(a) Center of Pressure on slope (b) Up-slope walking (c) Down-slope walking

Fig. 1. The AIDER exoskeleton.

Fig. 2. How to plan gaits on slopes with different gradients?



Fig. 7. Stick diagram presentation of simulation model walks over a 8° slope, the foot trajectories generated by DGG for up-slope and down-slope are shown in two bottom figures.



Fig. 8. Illustration of the Orbital Energy (OE) and the external force exerted to the model that changes over time while the simulation model walking on the 8° slope. T_1 , T_2 and T_3 are the moment of exerting external force, releasing external force and exchanging the support leg, respectively.



Experimental Results & Discussion







Fig. 3. Diagram of the Dynamic Gait Generator, which comprises two parts. In the first part, the humanexoskeleton system is modeled as a 2D-LIPM with an external force. The second part is the adaptive gait planning approach based on DMPs. It generates adaptive gaits by the given desired step time, the reference foot location and a normal walking gait trajectory sampled from normal human.



Fig. 5. The COM of the 2D-LIPM moves on a constraint line $z = z_0 + k \cdot x$ on slopes, where $k = \tan \theta$ and the θ is the gradient of the slope. In upslope case, k > 0, and in down-slope case, k < 0. Po and P_{cp} are start and reference foot locations for next step of swing leg, respectively.



Fig. 4. Human-exoskeleton model on a slope, which can be simplified as a 2D-LIPM, where θ is the gradient of the slope.



1.0

0.0

Fig. 6. In order to generate human-like natural gaits for patients, we sampled some healthy volunteer's gaits of normal walking on the level ground by the motion capture system Vicon. As shown in Fig. 6, we normalized the gait trajectories to some demonstrated trajectories for DGG. After learning from the demonstrated trajectory, the DMPs can reproduce trajectories adapt to the new start and goal positions, respectively.

x (m)



Acknowledgment

2017YFB1302300).

Fig. 9. The AIDER exoskeleton system: 1.The subject; 2.The crutches; 3.The embedded computer and IMU sensor in the backpack; 4.DC servo motors; 5.Angle encoders for each joint; 6. Smart shoes with plantar pressure sensors inside.

Fig. 10. We built five experimental slopes with the gradient from 4° to 12°, for each slope, the length of up-slope and down-slope is 3.6 meters, the slope width is 1.5 meters. And We invited some healthy subjects to simulate paraplegic patients (they were instructed to not use voluntary leg movement) and test the proposed approach on the AIDER exoskeleton system. Fig. 10. presents sequential snapshots of a subject walking up and down the 6° slope.



Fig. 11. The reference foot trajectories and actual foot trajectories on the 6° slope for both up-slope and down-slope in Cartesian space. Fig. 12. The actual OE could converge to the desired OE with the control of proposed approach while walking on different slopes.

This work was made possible by the support from NSFC (No.6150020696,

61503060), The National Key Research and Development Program of China (No.

Conclusions

In this paper, we modeled the human-exoskeleton system as a 2D–LIPM with an external force, calculated the reference foot locations for each step online, and employed the DMPs to model and reproduce adaptive gait trajectories for lower-limb walking assistance exoskeletons on slopes with different gradients.

Selected References & Contact Information

S. Kajita and K. Tani, "Study of dynamic walk control of a biped robot on rugged terrain using the linear inverted pendulum mode," *Transactions of the Society of Instrument & Control Engineers*, 2009.
M. Morisawa, et. al., "Balance control based on capture point error compensation for biped walking on uneven terrain," in *IEEE-RAS International Conference on Humanoid Robots*, 2012, pp. 734–740.
J. E. Pratt, et. al., "Towards humanoid robots for operations in complex urban environments," *Proceedings of SPIE - The International Society for Optical Engineering*, pp. 769 212–769 212–10, 2010.
A. J. Ijspeert, et. al., "Dynamical movement primitives: Learning attractor models for motor behaviors," *Neural Computation*, vol. 25, no. 2, pp. 328–373, 2013.
R. Krug and D. Dimitrov, "Model predictive motion control based on generalized dynamical movement primitives," *Journal of Intelligent & Robotic Systems*, vol. 77, no. 1, pp. 17–35, 2015.





GitHub ResearchGate

WeChat