IDENTIFICATION OF SWING LEG FEEDBACK CONTROL IN HUMAN WALKING

Huawei Wang and Antonie J. van den Bogert

Department of Mechanical Engineering
Cleveland State University, Cleveland, OH, USA
email: huawei.wang.buaa@gmail.com, web: http://hmc.csuohio.edu/

INTRODUCTION

The performance of humanoid walking robots has substantially improved in the past 10 years. One important reason is the use of stepping strategies to avoid falling by making a step to the right location at the right time. In the step strategy, capture theory is widely used [1], in which a simple model, for instance, linear inverted pendulum model (LIPM), is used to represent human walking dynamics and to estimate the desired foot location[2]. However, this control strategy includes many assumptions which have not been proven or tested in human walking. For example, the estimation of the desired foot location is based on the capture point, which means the LIPM will stop at middle stance [2]. However, the pelvis speed of humans will keep a relatively constant speed in walking.

This study will identify the swing leg control strategy from human walking data. By doing the identification, a stepping strategy can be obtained that does not rely on the hypothesis in the capture theory and simple models. Furthermore, since the identified control strategy is directly from human experiment data, it is more likely to generator human-like motions.

METHODS

The data used in this study is from a human walking experiment under random perturbation[3], in which human motion was recorded while walking with perturbed speeds. Random perturbation can trigger the human control system to generate more information into the walking motion. More general walking controller can be identified using this data than using non-perturbed data.

An indirect identification approach was used in this study to avoid the bias of direct identification[4]. For the indirect approach, a closed-loop system including human walking dynamics, stance leg torques, and swing leg feedback controller were built to represent the human walking system. Human dynamics was simplified to a two dimensional seven-links gait model. The stance leg was controlled by open-loop torques. Control parameters in the swing leg feedback controller were the targets of the identification. The indirect identification approach can be treated as an optimization problem, in which control parameters are optimized by minimizing the difference between the model output and the experiment data. The best control parameters are those who can make the close-loop model generate the same walking motion with experiment data under the same perturbation. The diagram of the indirect identification approach is shown in Fig 1.

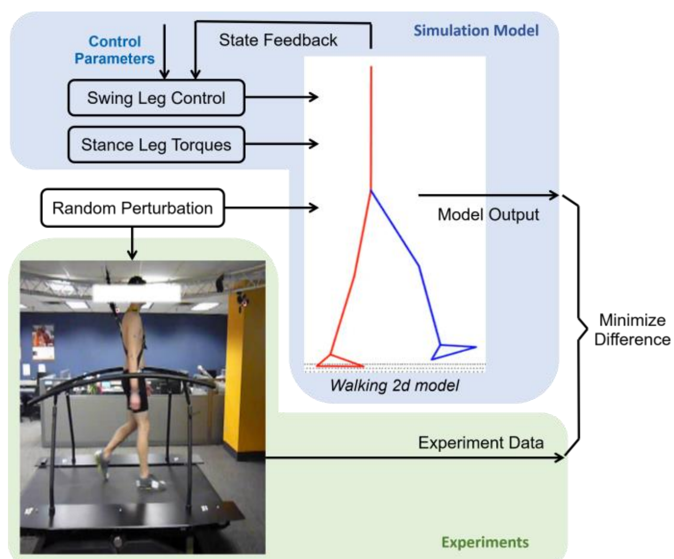

Figure 1. Indirect approach of swing leg control strategy identification.

The structure of swing leg control strategy is shown in Fig 2. It includes a foot location predictor, a swing path generator, an inverse kinematics module, and a local PD tracking controller. The foot location predictor predicts desired foot location based hip position and velocity, which shows in follow:

$$x_{target} = K_{p,swing} \cdot x_{hip} + K_{d,swing} \cdot \dot{x}_{hip}$$

The swing path generator generates the swing trajectory based on the desire foot location and swing time. Furthermore, it calculates current swing foot position based on the current swing timing. Swing path is defined by scaled polynomials which extracted from the experiment data. Inverse kinematics module resolves the joint angles of the swing leg to match with the current swing foot position. Local PD controller controls joints of swing leg to track the desire swing leg paths. Control parameters in desired foot location predictor and local PD tracking controller are identified in this study.

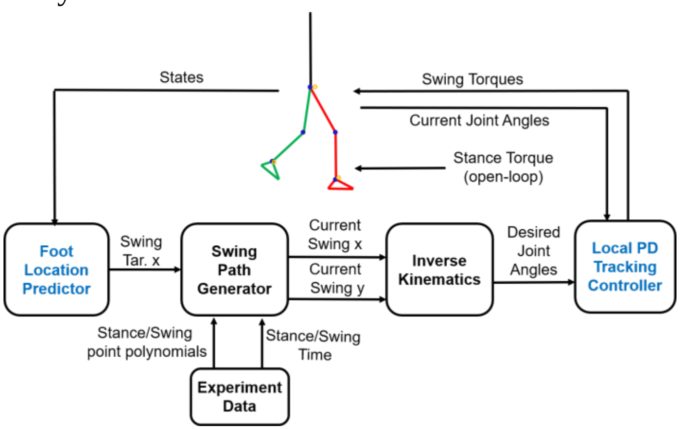

Figure 2. Control structure of gait2d walking motion.

RESULTS AND DISCUSSION

Identification was applied on 10 seconds walking data of a young female subject (64.5 *kg* and 1.72 *m*). Ten identifications with random initial guesses were done to avoid local optimum. The R^2 between most identified trajectories and experiment data is 0.95, which means that the identified control parameters produce perturbation responses that agree well with the experimental data. Means and standard deviation of the identified parameters in foot location predictor and local PD tracking controller are shown in table 1.

Table 1: Swing leg control parameters of a female subject

	Swing leg controller	Local PD controller	
		Hip	Knee
Proportional(K_p)	1.43 ± 0.02	1270 ± 274	1451 ± 403
Derivative (K_d)	0.43 ± 0.06	500 ± 0.06	417 ± 114

The identified result shows that the desired swing foot location can be calculated by a linear combination of 1.43 times hip position and 0.43 times hip velocity. These parameters are quite consistent among most identifications. In capture theory, LIPM suggests that linear combination gains are both 1.0. This means humans use different gains to predict foot location than capture theory. Humans relays more on position information and less on velocity information comparing to the LIPM.

Identified local PD control parameters have a large variation among optimizations with different initial guesses. However, local PD controller is not critical in the swing leg control, as long as it can make the swing leg following the desire swing path.

CONCLUSIONS & FUTURE WORK

In this study, swing leg control parameters were directly identified from human waking data. The identified swing foot location estimator has similar gains with capture theory (LIPM), but relays more on the pelvis position information and relays less on the pelvis velocity information. This work shows that directly identify controller from human experiment data is valid.

For future work, will test the identified swing leg controller by doing forward simulations. Another plan of this research is to apply this identification method on walking experiment data of different subjects with multiple speeds.

REFERENCES

1. Robert J. Griffin, et al. *IROS, 2017.*
2. Twan Koolen, et al. *IJRR, 2012.*
3. Jason Moore, et al. *PeerJ* **3(8)**: e918, 2015.
4. Herman van der Kooij, et al. *J Neuroscience Methods* **145** 175-203, 2005.

ACKNOWLEDGEMENTS

This work is supported by National Science Foundation under Grant No. 1344954 and by the Parker Hannifin corporation.