A2-1 ID82

AN INTELLIGENT TREADMILL SYSTEM FOR RUNNING TRAINING: CONTROL OF BELT SPEED AND BIOFEEDBACK

Akinori Nagano, Shoichi Kato, Kazutaka Iwao and Zhi-wei Luo

Department of Computational Science, Graduate School of System Informatics Kobe University, Kobe, Hyogo, Japan

We developed an intelligent treadmill system to realize more comfortable and safer running exercise. In the first part, we developed an algorithm to estimate the intended running speed of the user. We used the relation between the forward impulse of ground reaction force during the stance phase, stance time and swing time to estimate the intended running speed. We implemented the algorithm to an instrumented treadmill. In the second part, we evaluated the effects of real-time biofeedback of the mechanical stress on the legs. Initial peak of ground reaction force and leg stiffness value calculated based on the mass-spring model was visually shown. The subjects were instructed to reduce these values. It was found that initial peak of ground reaction force as well as leg stiffness can be effectively adjusted using visual biofeedback.

KEY WORDS: ground reaction force, running injury, leg stiffness.

INTRODUCTION: Running is a popular form of exercise that people can start relatively easily. Treadmill is a well-known equipment utilized to perform running exercise indoors. Typically the belt speed is controlled by the users with such interfaces as buttons, touch panel monitors etc. Users manually set the belt speed and adjust their running motion to the speed. Although it is true that people have got used to this interface, this is different from what we experience in normal overground running, in which we start from standing still, gradually increase the speed, and reach the desired speed. Even at the point, the running speed is not a constant value but fluctuates around the target. Therefore, behavior of the runners is assumed to be different between treadmill running and overground running. With this in mind, we set the first aim of this study as developing an intelligent treadmill that estimates the intended speed of the user. By estimating the intended speed and controlling the belt speed accordingly, running exercise on the treadmill can be made more realistic. We used an instrumented treadmill with force sensors, and used the ground reaction force (GRF) data for estimating the intention.
When considering running exercise, another important factor is running injury. There are a number of people who perform running regularly, and there exist a certain percentages of running injuries. It is assumed that these injuries partly come from the lack of knowledge of mechanical stress loaded on the legs during running. We set the second aim of this study as realizing a real-time biofeedback of the mechanical stress loaded on the legs during running. Specifically, (1) We aimed at analysing the mechanical stress on the legs real-time, using the intelligent treadmill. We calculated the initial peak of GRF and stiffness of the legs derived based on the mass-spring model. (2) We constructed a system of real-time visual biofeedback of the above mentioned variables. In addition, we tested the usefulness of the real-time system in adjusting running movement.
To summarize, we had two purposes in this study. First, we developed an intelligent treadmill that estimates the intended speed of the runner. Second, we developed a real-time biofeedback system of the mechanical stress on the legs. We set our goal as making running training on a treadmill more comfortable and safer.

METHODS: We performed this study in two phases. In the first phase, we developed a system to estimate the intended running speed using the signals from force sensors. In the second phase, we developed a system to realize real-time biofeedback.

Development of the Intelligent Treadmill: We measured GRF during running to find the essential factors for estimating the intention of the runner. We used a split-belt instrumented treadmill (ITR3017, Bertec; Figure 1). The treadmill has built-in force sensors and can output 6 components (3 force components and 3 moment components) for each leg real time. The data were taken into a personal computer using an A/D converter and house-made computer programs (LabView, National Instruments). We set the belt at constant speeds, and instructed the participants (seven males) to run on the treadmill for two minutes. We set the belt speed at seven different values. We collected the data at 1000 Hz and used them for further analyses. Through the analyses, we found that there is a clear relation between the pattern of GRF and the running speed. Specifically, there was a clear linear relation between the forward impulse of GRF (i.e., time integration of the forward component of GRF) and the running speed. Similarly, there was a linear relation between stance time and running speed, as well as swing time and running speed. Therefore we constructed multiple regression equations that describes the relation between the (belt speed) and (forward impulse of GRF, stance time, and swing time). This approach is similar to our previous work (Dong et al., 2012). We implemented this equation into the control algorithm of the treadmill. This enabled adjusting the belt speed according to the GRF data. Thereafter, we performed an experiment to evaluate the utility of the system. We showed the target and present speed to the participants and instructed them to adjust the speed following the change of target.

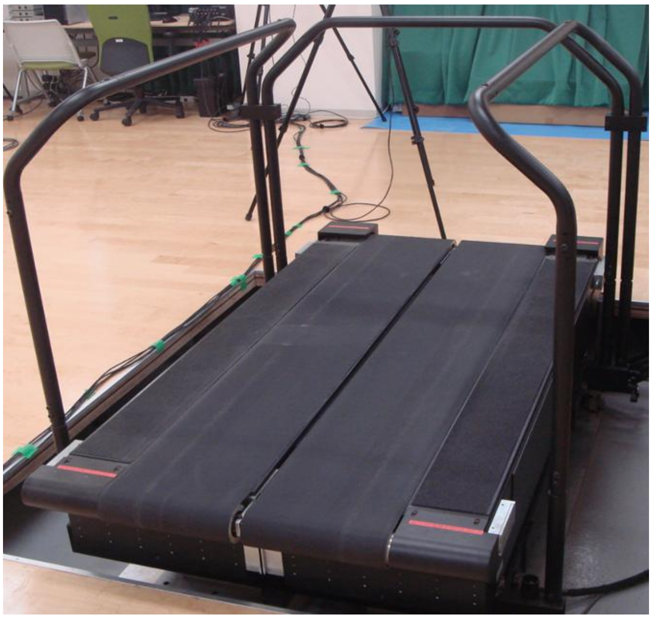

Figure 1. The instrumented treadmill used for this study. The left and right parts have individual sensors and control. Forces and moments data can be obtained.

Biofeedback on the Treadmill: For this part, we used the same treadmill and data processing tools. Initial peak of GRF (Lieberman et al., 2010) and stiffness of the leg based on the mass-spring model (Blickhan, 1989; McMahon and Cheng, 1990) were calculated from the GRF data. These data were presented on a large monitor placed in front of the subject (Figure 2, 3). The experiment was performed in three phases. (1) The participants ran on the treadmill for a few minutes, without visual feedback. They got used to running at the specific speed through this phase. (2) The participants ran on the treadmill with visual feedback. Their task

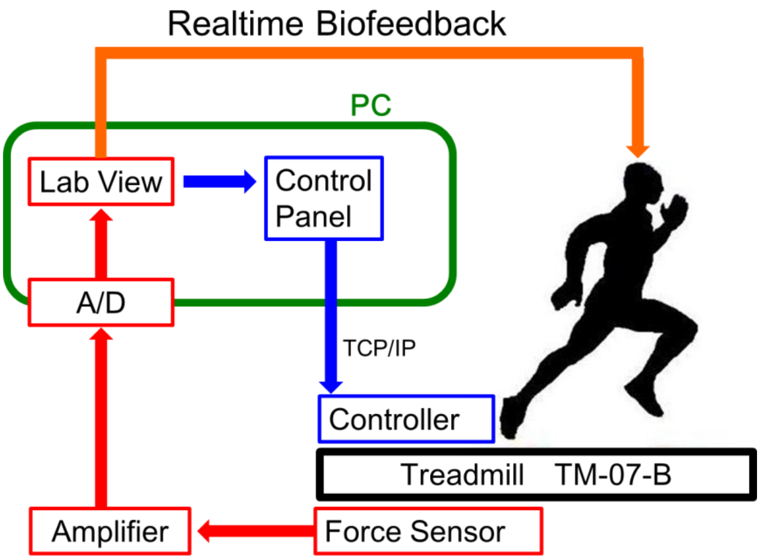

Figure 2. The system developed for this study. Real-time control and biofeedback was realized.

was to reduce the initial peak value of GRF. (3) The participants ran on the treadmill with visual feedback. Their task was to reduce stiffness value of the leg. Stiffness of the leg was calculated based on the data of belt speed and GRF. We asked the participants to repeat this procedure at three different speeds.

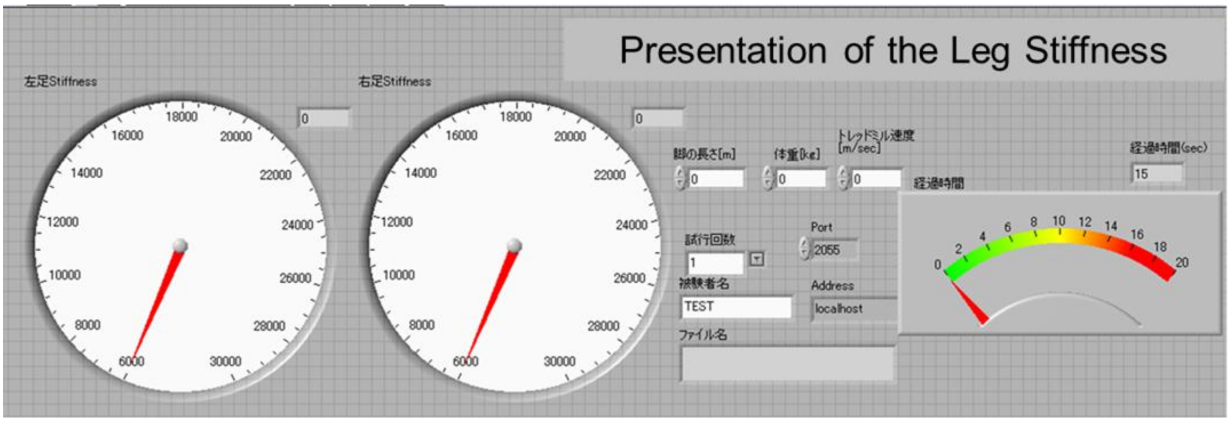

Figure 3. The indicator used for the presentation of leg stiffness. This view was displayed on a large monitor placed in front of the subject.

RESULTS: Control of the Belt Speed: The system developed in this study could successfully estimate the intended running speed. All the subjects could smoothly change the belt speed as they wished (Figure 4). The belt speed was successfully controlled around the target value, although there were substantial fluctuations. According to the questionnaire performed after data collection, the participants could run comfortably on the treadmill.

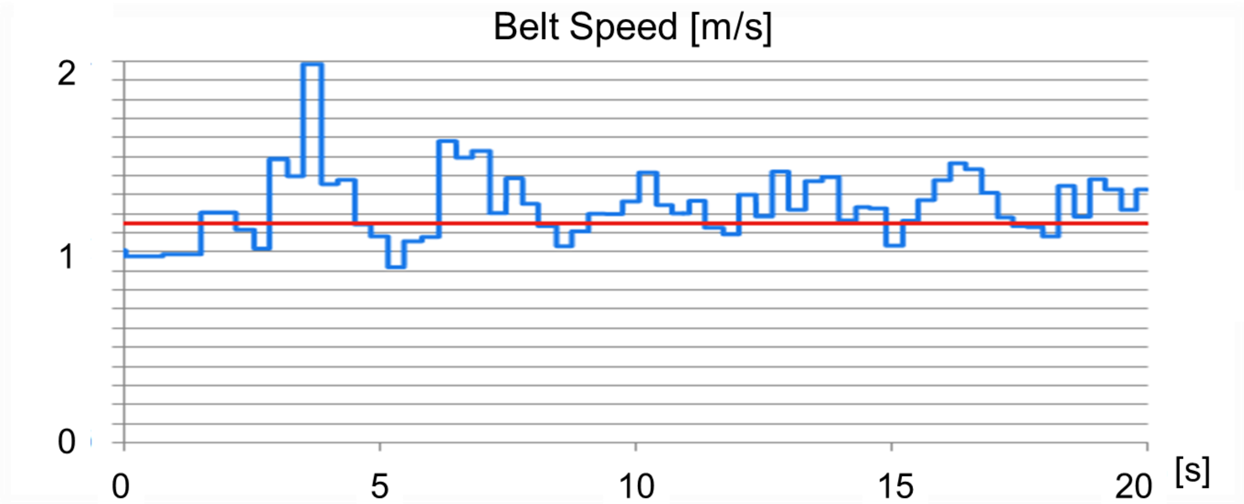

Figure 4. Result of the belt speed control during running. The speed was successfully controlled around the target value (straight line).

Biofeedback, Initial peak of GRF: The runners could clearly observe the value of initial peak of GRF in the monitor. We also found that the initial peak value of GRF was reduced with visual feedback. The effect was consistent in all the participants.

Biofeedback, Stiffness of the Leg: The runners could clearly observe the value of leg stiffness in the monitor. We also found that stiffness of the leg was also reduced with visual biofeedback. The effect was consistent in all the participants.

DISCUSSION:

Control of Belt Speed: It was possible to control the belt speed according to the intention of the user. As there were clear linear relationships between the belt speed and forward impulse, stance time and swing time, this was made possible. Also it might be possible to use other variables such as COP position and velocity, peak forces, etc. for the estimation. Or, the belt speed could be possibly controlled using a PID feedback controller based on the body position of the runner. This issue needs to be addressed in the future. As substantial fluctuations were observed in the belt speed in this study, it may be necessary to consider filtering of the speed control signal for even more comfortable use. As we aimed at evaluating the usefulness of intention estimation method itself in this study, we wanted to eliminate the effect of filtering for this report. This line of study can be further developed incorporating the technique of virtual reality (Dong et al., 2012).

Injury Prevention: It is hoped that this study contributes to reducing the cases of running injury in the near future. It became clear that the initial peak of GRF as well as stiffness of the leg can be adjusted with the clue of visual biofeedback. We still have not found the "optimal" values for the initial peak of GRF and the leg stiffness. Therefore we still do not know to what values these parameters should be adjusted. This issue needs to be addressed in future studies. Also, it might be useful to add accelerometer sensors as a part of the system, to obtain additional data regarding the motion of body segments (Crowell et al., 2010).

CONCLUSION: We developed an intelligent treadmill that estimates the intended running speed of the user. We constructed multiple regression equation and implemented it into the algorithm of belt speed control. The system successfully estimated the intended running speed and the users could comfortably run on the treadmill at the speeds they wished. We also found that visual biofeedback can be used to adjust the values of such mechanical stress as initial peak of GRF and leg stiffness. We aim to address the limitations of this current study and contribute to realizing an even better running training system i
n the future.

REFERENCES:

Blickhan R. (1989). The spring-mass model for running and hopping. *Journal of Biomechanics*. 22, 1217-1227.

Crowell HP, et al. (2010). Reducing impact loading during running with the use of real-time visual feedback. Journal of Orthopaedic and Sports Physical Therapy. 40, 206-213.

Dong, H., et al. (2012). An adaptive treadmill-style locomotion interface and its application in 3D interactive virtual market system. Intelligent Service Robotics 5, 159-167.

Lieberman DE, et al. (2010). Foot strike patterns and collision forces in habitually barefoot versus shod runners. Nature. 463, 531-535.

McMahon TA and Cheng GC (1990). The mechanics of running: how does stiffness couple with speed? Journal of Biomechanics. 23, 65-78.

Acknowledgement

This work was supported by JSPS KAKENHI Grant Number 24680067, and the Descente and Ishimoto Memorial Foundation for the Promotion of Sports Science.