ESTIMATION OF RUNNING INJURY RISKS USING WEARABLE SENSORS

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This research estimates running pattern characteristics that relate to running injury risks quantitatively and simply from a real-environment running motion. Wearable inertial measurement unit (IMU) sensors are used to provide a simple measurement of the running patterns in a real environment. We then measure an experimental running motion in detail in the laboratory using both large-scale devices and wearable sensors, and build correlational models between the conventional parameters related to running injury risks and parameters from wearable sensors. These correlational models realize a quantitative and simple estimation of running pattern characteristics related to running injury risks from a real-environment running motion. Our models estimate that fatigue, grounding style, pronation, and grounding impact have a high correlation with injury risk by the conventional methods. A feedback of these parameters and shoe selection based on these information would contribute to a reduction of running injuries.

KEYWORDS: running injury risks, wearable sensors, correlational models.

INTRODUCTION: Many people enjoy running easily in shoes to improve their physical health, though running may result in physical injuries and disabilities. Many running injuries develop in the legs compared to upper extremities and back. The lower extremity injuries are caused by a fatigue, grounding style, pronation, grounding impact etc. and results in injuries such as a tibial stress fracture, foot plantar fasciitis, knee patellar femoral pain syndrome, and shin splints (Daoud et al., 2012; Hinterman et al., 1998). Sports-goods manufacturers offer various shoes to reduce these running injuries and develop shoe selection systems to provide shoes that are appropriate to specific runners' running patterns. For instance, Static Foot ID from ASICS assists shoe selection based on a static posture, and Dynamic Foot ID selects shoe using an optical motion capture system and a treadmill (ASICS co.). These systems require large-scale devices, and running patterns measured in laboratory environments differ from real-environment ones because of a physical and psychological conditions (Elliot et al., 1976). A real-environment measurement, analysis, and feedback system of running patterns would realize an assistance for individual runners to select shoes that are appropriate to their running patterns and reduce the running injuries.
This research estimates the running pattern characteristics quantitatively and simply in a real-environment running to reduce the running injury risks. The wearable inertial measurement unit (IMU) sensors realize simple running pattern measurements in real-environment running. We also measure the experimental running motion in detail using the large-scale devices and the wearable sensors in the laboratory and build the correlation model between the conventional parameters related to the running injury risks and the parameters from the wearable sensors. These models can estimate the running injury risks from the real-environment running quantitatively and simply and contribute to the reduction of running injuries.

METHODS: The running motion is captured by using the IMU sensor (TSND151, ATR-Promotion, Japan) at a rate of 1000 Hz, the commercial marker-based optical motion capture system with 15 cameras (VICON, Oxford, England) at a rate of 200 Hz, and the force plate (AMTI, MA, USA) at a rate of 1000 Hz on ten adult male subjects (average ± SD; age: 24.5 ± 2.8 years, 172.1 ± 6.5 cm, 67.6 ± 11.5 kg). The subjects were free of any injuries at the time of data collection. Our study protocol was approved by the local institutional review board, and it conformed to the guidelines of the Declaration of Helsinki (1983). These devices were accurately synchronized using VICON MX system. The measured data were post processed using MATLAB2017a (The MathWorks Inc., MA, USA). As for the IMU sensors, we applied the 4-th order lowpass Butterworth filter with the cut-off frequency of 50 Hz to the acceleration, and the 4-th order bandpass Butterworth filter with the range of 1 Hz to 50 Hz to the angular velocity. The ground reaction force data were filtered with the 4-th order lowpass Butterworth filter with the cut-off frequency of 50 Hz (Nordin et al., 2017).

Hardware: Wearable IMU sensors (Figure 1) were applied to our system for a simple measurement of running pattern in a real-environment running and to measure accelerations and angular velocities of runners' foot segments. Running has a huge impact in the 10 to 30 ms at grounding. The IMU were TSND151 (ATR-Promotion, Japan) that have a high sampling rate (up to 1000 Hz) and a large measurement range. Peak acceleration at the grounding exceeds the acceleration range of TSND151 (16G), and we interpolated the acceleration with a spline function when the huge acceleration is detected.

Software: Our system extracted the running pattern characteristics that are related to running injuries. Here, the fatigue, grounding style (rear foot strike (RFS), mid foot strike (MFS), and fore foot strike (FFS)), grounding impact, and pronation (overpronation and supination). These parameters were computed using the large-scale devices, for instance, optical motion capture systems and force plates. We measured running motion using the wearable IMU sensors and the large-scale devices simultaneously and built the correlation models between the parameters computed from these simple and large-scale devices. These models were used to realize the quantitative and simple estimation of running injury risks using wearable sensors.

Fatigue: We used a support-phase duration as the indicator of fatigue. This support-phase duration represented the rate of support phase during one running cycle and correlated with the running speed, as well as the fatigue. The conventional method computes this support-phase duration from the grounding and take-off time measured using the force plate. The improved algorithm of S-method (Mo et al., 2018) was applied to this system. The grounding time was computed as the rising time just before the acceleration peak, and the take-off time is the peak time just after exceeding 2G after the grounding. We computed the support-phase duration based on these grounding and take-off times.

Grounding style: There are three different grounding styles, RFS, MFS, and FFS, and possible injuries and suitable shoes differs between them. The conventional method recognizes these styles from Strike Index (SI) that is computed using the optical motion capture system and the force plate (Altman et al., 2012). This SI is a rate of a distance between a centre of pressure from a heel at the grounding w.r.t. a foot length. The system in our study estimates this SI from a plantar / dorsal-flexion behaviour of a foot segment at the grounding that is measured by IMU sensors. The foot segment grounds at the dorsal-flexion posture and keeps plantar flexion in RFS. On the other hand, the segment grounds at the plantar-flexion posture, once dorsal flexes, and then plantar flexes. We focused on these behaviours and computed θ_{IMU} as shown in Figure 2. The correlation model between SI from the conventional method and θ_{IMU} estimates SI from θ_{IMU} measured by IMU sensors.

Figure 1: IMU sensors on shoes

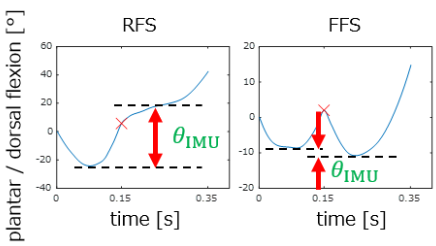

Figure 2: plantar / dorsal flexion of RFS and FFS

Grounding impact: The grounding impact that relates to the tibia fatigue fracture is represented by the vertical force impact peak (VIP), the vertical average loading rate (VALR), and the vertical instantaneous loading rate (VILR) (Davis et al., 2015; Bonanno et al., 2016; Crowell et al., 2010). The conventional method computes the vertical gradient of the grounding reaction force at 20% to 80% of its first peak at the grounding using the force plate. The system used in our study estimates VALR from the peak acceleration of the foot segment measured by the IMU sensor. Here, we use the peak of acceleration norm (PA) because of the integration error of the angular velocity from the IMU sensor.

Pronation: The pronation is the complex compound motion with the extroversion of the calcaneus and the plantar flexion and adduction of the talus and often observed on the RFS runners. The excessive overpronation collapses the foot arch and triggers the risk of the plantar fasciitis, the Achilles tendonitis, the knee patellar femoral pain syndrome, and the shin splint (Daoud et al., 2012; Hinterman et al., 1998). The conventional method measures the angle between the heel and the calf at the grounding with two markers on each segment using the optical motion capture system and the force plate (θ_{pro}). The system used in our study estimates the pronation from the angular velocity in the coronal plane using the IMU sensor. The angle between the heel and the calf correlates highly to the peak value of the angular velocity in the coronal plane (Shin et al., 2014). The peak angular velocity within ± 20 ms around the acceleration peak at the grounding (ω_{peak}) are applied to build the correlation model with the angle between the heel and the calf. The standard linear regression models are applied to examine the relationships between the convention and IMU estimation methods using MATLAB2017a (The MathWorks Inc., MA, USA).

RESULTS: Figure 3 shows the error between the grounding and take-off time that is measured using the force plates and the ones estimated from the IMU sensors data, whose positive value represents the time delay. We apply the S-method and our method to the IMU sensors data and compare these results.

Figure 4 shows the SI computed by the conventional method and θ_{IMU} that is computed from the IMU sensors data. The correlation between these data is SI = 0.00162 X θ_{IMU} + 0.697 and its correlation coefficient is r = 0.900 and RSME = ±0.116. Figure 5 shows the grounding style estimated by the SI and our method. The green, orange, and cyan points represent RFS, MFS, FFS respectively, that are estimated by the SI. The green, orange and cyan area represents RFS, MFS, FFS that are estimated by our method.

Figure 6 shows the VALR computed by the conventional method and the PA from the IMU sensors data. The correlation between these data is VALR = 2.45 X PA + 35.8 and its correlation coefficient is r = 0.460 and RSME = ±16.9 BW/s.

Figure 7 shows the θ_{pro} computed by the conventional method and the ω_{peak} computed from the IMU sensors data. The correlation between these data is θ_{pro} = 0.0231 X ω_{peak} + 6.67 and its correlation coefficient is r = 0.800 and RSME = ±2.19°.

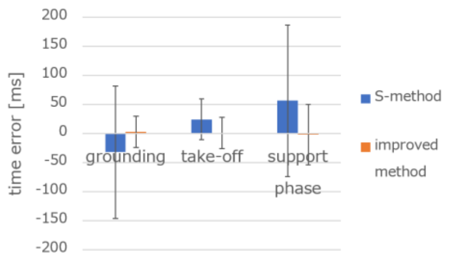

Figure 3: Support-phase duration

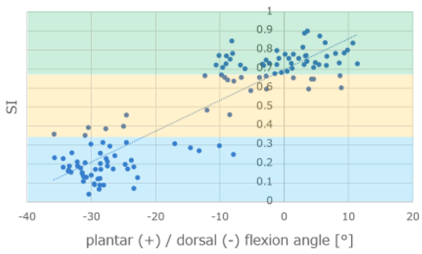

Figure 4: SI and plantar / dorsal flexion

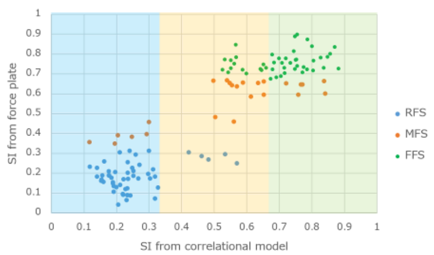

Figure 5: SI estimation

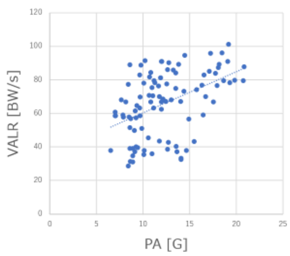

Figure 6: VALR and PA

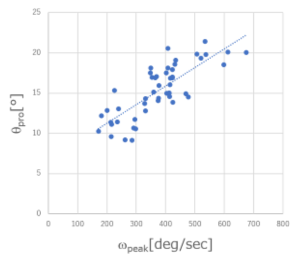

Figure 7: θ_{pro} and ω_{peak}

DISCUSSION: S-method estimates the grounding and take-off time within the error of -32.2 ± 114 ms and 24.2 ± 35.3 ms (average ± SD), and our method realizes the error of 2.34 ± 27.0 ms and 0.570 ± 27.0 ms (Figure 3). This result shows that our method improves the accuracy of the support-phase duration estimation. The grounding style was estimated with the correlation coefficient of r = 0.900, whose estimation using the optical motion capture system was r = 0.930. Our method with the wearable IMU sensors realizes the similar estimation accuracy compared to the large-scale devices. The grounding impact estimated by our method has the intermediate correlation (r = 0.460) with VALR. This may be because we used the peak of the acceleration norm and the horizontal acceleration of the braking effects on this result. Implementing the posture estimation of the IMU sensors and estimating the vertical acceleration would improve the VALR estimation. Our method estimates the pronation with a correlation of r = 0.800, and this result implies the high correlation between the peak value of angular velocity in the coronal plane and the angle between the heel and the calf measured by the optical motion capture system.
These results show that the simple measurement using the IMU sensors realizes the quantitative estimation of the fatigue, the grounding style, the grounding impact, and the pronation.

CONCLUSION: This paper developed the system that realizes the quantitative and simple measurement of the real-environment running pattern and estimates the running injury risks using the correlation model with the conventional parameters that are computed using the large-scale devices. Our system estimated the fatigue, grounding style, grounding impact, and pronation which was highly correlated with the conventional methods. Real-time feedback and a shoe selection system based on this information would contribute to the reduction of running injuries.

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