REAL-TIME BACKWARD SLIP DETECTION USING A SLIP-INDUCING SYSTEM AND MACHINE LEARNING METHODS

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Wearable devices have been developed to assist walking based on the wearer's intention. However, it would be dangerous if a device misidentifies falling as intentional motion; it is necessary to detect falls in real time. In particular, backward slip is the most common and dangerous type of falls. Fifteen participants walked on a split-belt instrumented treadmill while random backward slip perturbation of belt speed acceleration was provided to the foot. We aimed to identify slip within 0.35s after the onset of the perturbation, the typical window of slip, using lower limb kinematic data obtained within 0.3s; only 0.05s was allowed for the identification. We developed 5 machine learning models, and the logistic regression model showed the highest accuracy of 87.5%. The initial study is expected to contribute to the prevention of falls by developing and applying the results to wearable devices.

KEYWORLDS: gait, falls, split-belt treadmill, kinematics, acceleration

INTRODUCTION: More than 32% of the elderly aged 60-97 have gait disorders that are associated with reduced mobility, depression, diminished quality of life, and falls (Mahlknecht et al., 2013). To contribute to solving this important problem, wearable robots that detect wearer's intention and give assistive force are being developed. For example, GEMS-hip (Samsung Electronics Co., Ltd.), which provides additional power during walking, is light enough to use in everyday life and workout. However, despite such progress, there are still important challenges to be solved. Falls can occur anytime during various activities including walking throughout all ages (Talbot et al., 2005); especially more than 20% of the elderly fall at least once a year (Jia et al., 2019). In particular, backward falls are much more dangerous than forward falls because they cause back, hip and head injuries. The resulting injuries (e.g. hip and skull fractures) and aftereffects can even lead to death. Mental problems such as fear of falling lowers the quality of life and changes human behavior patterns. Among the various types of falls, slip accounts for 55% of all falls, which is more than twice of trip (22%), which accounts for the second largest (Courtney et al., 2001). In addition, the worker's compensatory cost associated with slip in industrial field is greater than the sum of all other types of falls (Amandus et al., 2012). Therefore, among various types of falls, backward slip needs to be predicted and prevented with the highest priority.

There have been attempts to predict or quantify falling. A previous research (Özdemir & Barshan, 2014), succeeded in identifying falls with 99% accuracy using inertial measurement unit (IMU) sensor data of 2s before and after the maximum acceleration point. Another study (Martelli et al., 2014) identified falls with 95% accuracy using the acceleration of each body segment's center of mass (COM) of 5s before and 1s after falling. However, in actual walking, falling happens much faster than the time interval required in these previous studies; the suggested identification methods cannot prevent injury due to falling. Another limitation of previous fall-related studies is the lack of precise control of the applied perturbation. Multiple studies used mechanical obstacles, cables, slides and contaminated floor to cause slip (Myung, 2003; Yang & Pai, 2011). In these kinds of experimental set-up, the intensity, onset time and direction of the perturbation could not be precisely controlled.

Motivated by these limitations of previous studies, we aimed to 1) develop a slip-inducing system that can apply precisely controlled slip stimulation and 2) propose machine learning models that can reliably predict falling within sufficiently short time interval so that prediction can be completed before falling causes injury. Specifically, considering that slip typically occurs within 0.35s after stepping on the ground, we aimed to predict falling using data of 0.3s. By the way, although prediction using machine learning yields higher accuracy than threshold methods, such approach requires sufficient data (Aziz et al., 2017). We hypothesize that the data we will collect using our automatically controlled slip-inducing system enable us to develop machine learning models that can accurately predict backward slips within 0.05s using the data collected during 0.3s.

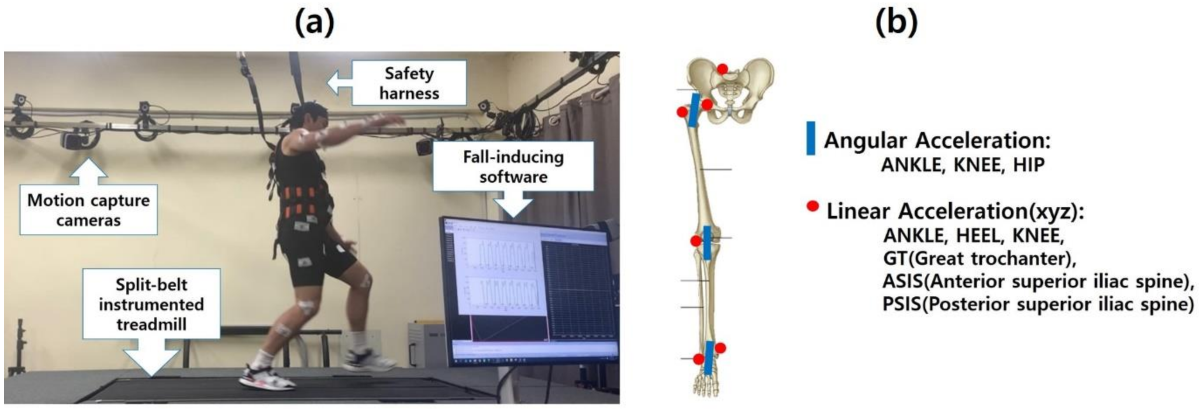

Figure 1. (a) Experiment setup (b) Reflective markers and features used for prediction

METHODS: Figure 1(a) shows our customized slip-inducing system. It consisted of programmable instrumented split-belt treadmill (Bertec Corporation, Columbus, OH, USA), the Qualisys motion capture system with 9 cameras (Qualisys, GBG, Sweden), and MATLAB software (Mathworks Ltd., MA, USA). Ground reaction forces (GRFs) were measured at a rate of 1000Hz and were sent to the PC that was linked with motion capture system. The moment when the GRFs exceed 2% of body weight was defined as the moment of heel strike. The system controls the treadmill belt speed acceleration to give participants backward slip stimulus at any heel strike chosen by the experimenter. There were 4 kinds of perturbation: left large (LL), left small (LS), right large (RL) and right small (RS), which were normalized by subject's preferred walking speed (PWS). Treadmill returned to the original state with deceleration of 10 m/s^2 after 0.35s or at the end of the slip.
Fifteen young and healthy adults (25.2±3.4 years old; 178.6±4.6 cm; 78.7±8.2 kg), who never have been experienced neurological disorders, musculoskeletal dysfunctions and injuries that can impact walking pattern in the past 1 year participated in this study. This study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board. All participants reviewed and signed the informed consent prior to the participation. We attached 47 reflective markers to the participants who wore safety harness and measured their PWS. Participants walked at PWS for 6min for adaptation (Meyer et al., 2019). Then, participants completed 4 sets of 6 trials. Each trial consisted of walking (20~30s at PWS), slip perturbation (0.35s) and recovery (defined as the time interval from the moment when perturbation removed to the moment when the GRFs return to the original state (Lee et al., 2017)). Our system randomly applied slip perturbation to the participants after walking period. Each perturbation was given 4 times equally, with 8 non-slip trial to erase learning effect. Each set lasted approximately for 6min with at least 5min rest between sets.
Motion capture data for 0.3s after stimulation were collected at 500 Hz. Linear acceleration of markers in the x, y, z directions and angular acceleration (Figure 1(b)) were computed by MATLAB. Minimum, maximum, mean, variation, skewness and kurtosis values of the data were then calculated to be used as features in machine learning (Özdemir & Barshan, 2014). For the answer data to determine whether or not slip occurred, the force applied to the harness was calculated by subtracting the sum of the GRFs on both treadmill belts from the net force applied to the whole body, which was the acceleration of COM multiplied by the body mass. If this force on the harness exceeded 30% of the body weight, it was primarily judged as a possible slip. Among the cases classified as possible slip, if the force was less than the average + 3SD (standard deviation) of none-slip in any case, it was judged that the participant had recovered from the risk of falling and the case was classified as none-slip (recovery) (Yang & Pai, 2011).

The Five machine learning algorithms – the k-nearest neighbor classifier (k-NN), support vector machine (SVM), logistic regression (LR), random forest (RF), extra gradient boost (XGB) were chosen to determine if the case was slip or not. These are representative machine learning algorithms for data classification and have shown good performance in previous studies (Chen & Guestrin, 2016; Özdemir & Barshan, 2014). Data were divided into 80% training and 20% test data. Then, the training data were divided into training and verification data again, and cross validation was performed K times; K was selected as the number of repetitions of the calculation that yielded the highest accuracy for each machine learning model. The initial test data were used only to evaluate the final model. We evaluated five machine learning algorithms using accuracy, f1-score, calculation time and area under curve (AUC). The closer the f1-score is to 1, the more unbiased the data are. By comparing the AUC value, which is the area under the ROC curve[1] with a value between 0 and 1, whether the threshold value for determining slip is appropriate can be assessed.

Table 1. Performance of models whose features are (a) angular acceleration or (b) linear acceleration

Feature	(a) Angular Acceleration						(b) Linear Acceleration					
Model		k-NN	SVM	LR	RF	XGB		k-NN	SVM	LR	RF	XGB
		P N	P N	P N	P N	P N		P N	P N	P N	P N	P N
Confusion Matrices	P	30 11	32 6	32 6	34 4	33 5	P	34 7	35 3	35 3	34 4	34 7
	N	15 16	10 24	13 21	9 25	9 25	N	7 24	7 27	6 28	6 28	6 28
Accuracy (%)		0.6389	0.7778	0.7361	0.8194	0.8056		0.8056	0.8611	0.8750	0.8611	0.8194
f1-score		0.6977	0.8	0.7711	0.8395	0.8250		0.8293	0.8750	0.8861	0.8718	0.8267
Time (s)		0.0054	0.0022	0.0011	0.0224	0.0083		0.0103	0.0016	0.0021	0.0203	0.0020
AUC		0.87	0.95	0.95	0.93	0.91		0.71	0.85	0.90	0.87	0.84

P = Positive, N = Negative

RESULTS: All 15 participants completed 24 trials without giving up. However, a total of 356 trials data were used for analysis, excluding 4 trials data that could not be used due to errors in data collection. There were 190 none-slips and 166 backward slips. Table 1 shows that machine learning models with the features of linear acceleration generally performed better than those with the features of angular acceleration. The LR model with the features of linear acceleration showed the highest accuracy of 87.5%. It also showed the highest values of f1-score and AUC among the five models using linear acceleration. Among the models using angular acceleration as learning features, the RF model showed the highest values in most performance indices though it took the longest time for calculation. All models completed the calculation within the target interval of 0.05s.

DISCUSSION: In the previous studies (Martelli et al., 2014; Özdemir & Barshan, 2014), fall was identified with an accuracy of over 99% and 95%. Although the 88% accuracy of machine learning models developed in our study is lower than the results of previous studies, it is noteworthy that the models developed in this study use data of a very short time interval of 0.3s and complete the identification within 0.03s. Direct comparison is not possible as there is no prior study using such a short time interval that applicable to real time. Follow-up studies to increase accuracy with more optimal input features and more suitable algorithms are needed. The main potential users of the wearable assistive devices are the elderly, and since their kinematic characteristics are different from young people, a future study should address the validity of the similar approach for the elderly.

[1] Receiver Operational Characteristic curve which represents the recall value compared to fall-out. If the threshold for predicting the correct answer of the model is lowered, the recall value, which is the sensitivity of model, increases. Simultaneously, the fall-out, which is the probability of incorrect answers, also increases.

CONCLUSION: As the average life expectancy increases in the coming future, more and more people will want to enjoy sports and leisure even with the help of equipment. The wearable devices can provide the proper assistance for these people. To ensure safety in such situations, it is essential to quickly identify any unwanted motion and send proper command to the actuators. As an initial attempt to actualize such necessary technology, we suggested a method for predicting slip in real-time.

We devised a slip-inducing system that can apply controlled perturbation at the automatically detected moment of heel strike. Then, exploiting this system, we collected gait data with and without an occurrence of falling. Using these data, we developed machine learning models that predict falling with accuracy of 80~90% within 0.05s only with features collected during 0.3s. This result can contribute to preventing the assistive wearable devices from misidentifying the falling as an intended motion, amplifying it and thus increasing the risk of injury.

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