

Stair descent detection using foot-worn inertial sensors

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Abstract—The correct detection of locomotion modes is important for activity evaluation of daily life. This study presents a simple method for identifying stair descent activity using shoe-based inertial sensors. Activity data was recorded from four young participants, performing sitting, standing, level walking at different speeds, stair climbing and stair descending. It was hypothesized that during the stair descent the pitch angular velocity of the foot has a pattern that is different from level walking and stair ascent. A pattern recognition algorithm based on peak detection was designed and tested on the recorded signals. Compared to externally labeled data (reference) the maximum sensitivity for stair descent detection was 92% when identifying single cycles and 98% when identifying locomotion periods. The specificity was 100% in both situations. This result is encouraging for more extensive activity classification and locomotion mode recognition using inertial sensors attached to the shoes.

Keywords-Activity Recognition; Wearable Sensors; Locomotion Mode; Stair Descent

1 INTRODUCTION

The importance of characterizing human physical activity and locomotion modes has been recently highlighted in many clinical studies such as fall and fracture prevention [1], chronic pain [2] and general quality of life assessment [3]. Ambulatory monitoring of physical activity has seen major advances in recent years due to miniaturization of sensors and classification algorithm enhancements [4], [5].

Recognizing stair locomotion is an essential part of activity classification. From an energy expenditure point of view, ascending/descending stairs requires more energy than level walking [6], [7], with stair ascent requiring more energy than stair descent [8]. Stairs are also considered as obstacles [9] that require postural control to safely negotiate [10]. Furthermore, stair training and its evaluation is linked to fall prevention and assessment [11].

The detection of stair ascent/descent has been previously addressed with varying results in inertial shoe-based activity monitoring studies. Sensitivities ranging between 57.5%-68.8% for stair climbing and 71.3%-87.6% for stair descending were reported for healthy subjects wearing an ankle foot orthosis with different constraint types [12]. Using a gyroscope on the shank, Coley et al. report average sensitivities above 97% for stair climbing in three subject populations: healthy young, elderly with limited locomotion and elderly with chronic pain [9]. However, no detection of stair descent was achieved.

By hypothesizing that a specific pattern in the angular velocity of the foot exists, the objective of this study is to provide a new algorithm to detect stair descent using a single inertial sensor attached to the dorsal aspect of the foot on the shoe. Together with existing algorithms for level walking and stair ascent, the present study can further improve the accuracy of wearable systems for daily life activity classification.



Figure 1-a) Physilog® with data logger, b) Physilog® inserted in a strap, c) Sensors attached to participant's feet, d) Staircase used for monitoring stair descent and ascent. Note the level platform in the middle of the stairs.

2 MATERIAL AND METHODS

2.1 Activity protocol and sensors

Four male subjects (age 26.25 ± 3 , BMI 22.7 ± 2.3) were asked to perform a series of activities including sitting, standing (with Sit-to-Stand transitions), level walking (slow, self-preferred and fast speeds), stair descent and stair ascent. The staircase used for the protocol consists of 20 stair steps and is shown in Figure 1 (d). Subjects gave signed, written consent after being informed about the data collection methods and the study was approved by the ETH ethical committee. The activity sequence was controlled by the investigators and was identical between subjects. The activities were carried out indoors.

Each subject was equipped with two Physilog® inertial measurement units (Gaitup, CH, www.gaitup.com) strapped to each of the subject's shoes, as shown in Figure 1 (a,b,c). The Physilog® consists of triaxial accelerometer and triaxial gyroscope sensors along with data logging capabilities. Inertial sensor data was sampled at 200 Hz and low-pass filtered at 17 Hz.

Activities were labeled using an external pulse emitter to a third Physilog® data logger module synchronized with both feet mounted units. A start/stop code was used to annotate the activity sequences. These sequences were processed offline and the labeled reference activity data was obtained between each start/stop sequence, corresponding respectively to the beginning/end of each activity.

2.2 Detection algorithm

The algorithm devised to distinguish stair descent from level walking and stair ascent was based on the observation that the foot pitch angular velocity ω_p (rotation around the medio-lateral axis) during downstairs movement is different compared to level walking and stair ascent, which can be observed on the illustrative example in Figure 2. In fact, there is an abrupt change in the direction of foot rotation in the sagittal plane at the foot contact point, visible by the sudden change of the sign of angular velocity. The detection algorithm firstly detects a single gait cycle based on the Foot-Off (FO) instance appearing as the highest negative peak of the ω_p signal [13]. A complete cycle was defined as the interval between two consecutive FO instances with a duration of less than 2.5 seconds. Then, for each foot signal, a maximum and minimum peak search was performed between the consecutive FO of each cycle. A downstairs cycle was defined when the minimum peak preceded the maximum peak of ω_p in time. Otherwise, the cycle was labeled as walking/stair climbing and the rest of the data was labeled as non-locomotion. This segmentation method provided the first analysis stage by identifying the individual cycles for each foot.

The algorithm was further refined by defining locomotion as a minimum of three consecutive cycles within a time limit. In this case, periods of two cycles or less within 3 seconds of one another were labeled similarly to the previously detected activity. For example, if a single level walking cycles is detected between two episodes of stair descent (of more than 3 cycles, with less than 3 seconds between the level cycles and the stairs cycles), the period encapsulating the stair descent is considered entirely to be stair descent without interruption. This might occur when a staircase is not continuous, but has platforms in between stair groups, as in Figure 1 (d).

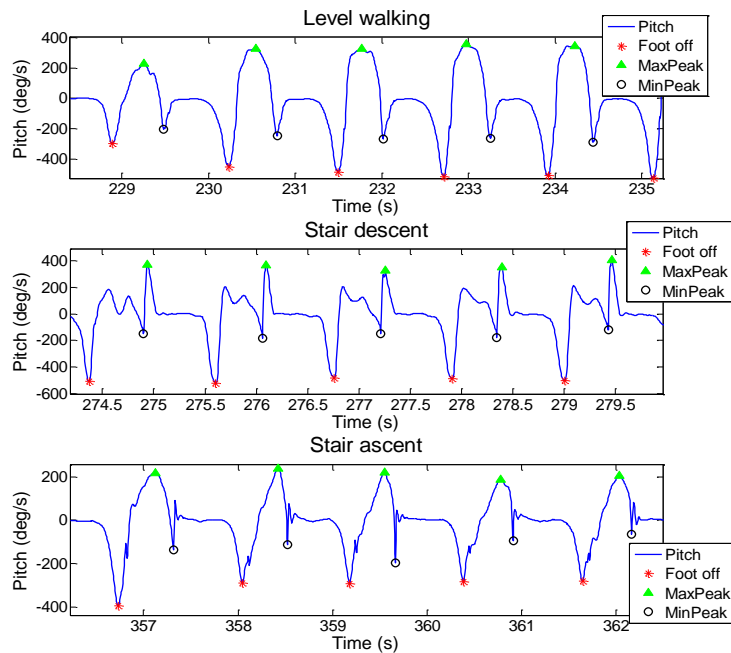


Figure 2-Pitch angular velocity for the different types of locomotion. Top: level walking, Middle: stair descent, Bottom: stair ascent. The Foot Off (FO), maximum and minimum peaks between two consecutive FO instants are also shown.

2.3 Sensitivity, specificity analysis

The performance of the stair descent detection was evaluated by calculating the sensitivity (proportion of correctly identified stair descent epochs to all recorded stair descent epochs) and specificity (proportion of correctly identified non-stair descent epochs to all non-stair descent epochs) for the cycle specific and period specific outputs. Here, the positive class is the stair descent, and the negative class contains walking, stair climbing and non-locomotion.

3 RESULTS

3.1 Individual cycle detection in stair descent

The sensitivity and specificity values from data recorded from each subject are indicated in Table 1. These values represent the detection of a single cycle between two consecutive FO instants as described in the methods section. On average, the sensitivity is higher than 80% for the left foot and higher than 92% for the right foot. The specificity is higher than 99% for both feet.

3.2 Stair descent period detection

After combining single cycle periods with their preceding activity labels, the new sensitivity and specificity results are presented in Table 2. An average sensitivity of 97.8% and 92.84% for the right and left foot, respectively, is obtained, with a specificity of 100% for both feet.

4 DISCUSSION AND CONCLUSION

In this study, accurate detection of stair descent was achieved with an average of almost 98% (on the right foot) using a simple method based on empirical observation of inertial signal features. Additionally, the specificity of 100% showed that there were relatively no false positives. Besides these good performances, the algorithm has the advantage of being suitable for ambulatory applications and can be used for activity recognition in everyday life.

From a kinematics point of view, this difference in pitch angular velocity between stair descent and other types of locomotion is due to the stair descent movement itself: while the foot is dropping down, the toe strike on the stair step occurs with a pitch angular velocity that is opposite to that of the foot segment movement. The obtained detection accuracy is an improvement on existing literature for stair descent detection using inertial sensors at the foot level: Using a 6D inertial sensor, Archer et al. reported a sensitivity of 71.3% for stair descent in 8 healthy subjects wearing an ankle orthosis in “free” condition that did not restrict their movements [12]. This sensitivity increased in constrained conditions, possibly due to more uniformity of the constrained stair descent. Tang and Sazonov report stair descent detection precision of 100% and recall of 94.2% using an MLP classifier with rejection, in 9 young and healthy subjects wearing a force sensing insole and a 3D accelerometer on the shoes [14]. However, before rejection of activity epochs (approximately 30% of the epochs were rejected), the precision and recall were 91.6% and 71.1%, respectively. A sensitivity of 84.5% for stair descent recognition was achieved by Lau et al. when compared to level walking and stair ascent in 7 stroke patients wearing a kinematic sensor at the foot level [15]. However, upon adding up slope and down slope activities, the sensitivity of stair descent recognition decreased to 53%.

Table 1-Sensitivity and specificity, per subject and per foot, for single cycle detection of stair descent

<i>Subject</i>	<i>Sensitivity, right</i>	<i>Specificity, right</i>	<i>Sensitivity, left</i>	<i>Specificity, left</i>
<i>1</i>	99.96	100.00	76.34	100.00
<i>2</i>	89.55	100.00	88.91	100.00
<i>3</i>	91.28	100.00	66.07	100.00
<i>4</i>	88.41	99.76	90.71	99.72
<i>Average</i>	92.30	99.94	80.51	99.93

Table 2-Sensitivity and specificity, per subject and per foot, for locomotion period detection of stair descent

<i>Subject</i>	<i>Sensitivity, right</i>	<i>Specificity, right</i>	<i>Sensitivity, left</i>	<i>Specificity, left</i>
<i>1</i>	99.96	100	88.92	100
<i>2</i>	100	100	99.96	100
<i>3</i>	91.28	100	82.48	100
<i>4</i>	99.96	100	100	100
<i>Average</i>	97.80	100	92.84	100

The slight difference in results between left and right foot could be due to the initiation and termination of the stair locomotion period. However, the algorithm should have an additional condition whereby the two feet should have the same locomotion mode within a time limit, as this will improve the detection accuracy.

The drop of accuracy when detecting individual cycles is due to the fact that during the downstairs locomotion periods, one or two cycles occur on the level platform and are identified (correctly with high accuracy) as level walking cycles; however, the reference label for the entire period is stair descent. Hence, by grouping disjointed locomotion events with a threshold on time or number of cycles, a high accuracy for stair descent period detection is achieved.

This work will be extended in several directions. First, the proposed method will be further validated by including more participants and more subject populations (e.g. elderly people and/or stroke patients), since negotiating stairs can be different for these populations (e.g. reaching each stair using both feet). Second, the methodology will be extended to the detection of stair ascent as in [9] since it will allow a better characterization of locomotion types. Furthermore, investigating the effect of sensor placement on the foot could provide interesting insights into the usability of the sensor. Also, a comparison of stair descent inertial signals with other spurious or confounding movements such as in place stepping would be interesting to further assert the specificity of the method.

This study is part of a project that aims to design a shoe-based system that fuses signals from inertial and foot pressure sensors to provide accurate activity detection for daily-life monitoring. The role of simple yet accurate detection of some locomotion types will provide a major benefit for long-term activity monitoring.

5 ACKNOWLEDGMENT

The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement FARSEEING n° 288940. The authors would also like to acknowledge Dr. Eling de Bruin for the ethical application that was required to perform the measurements.

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