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Instrumented shoes for activity classification in the elderly

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ABSTRACT

Quantifying daily physical activity in older adults can provide relevant monitoring and diagnostic information about risk of fall and frailty. In this study, we introduce instrumented shoes capable of recording movement and foot loading data unobtrusively throughout the day. Recorded data were used to devise an activity classification algorithm. Ten elderly persons wore the instrumented shoe system consisting of insoles inside the shoes and inertial measurement units on the shoes, and performed a series of activities of daily life as part of a semi-structured protocol. We hypothesized that foot loading, orientation, and elevation can be used to classify postural transitions, locomotion, and walking type. Additional sensors worn at the right thigh and the trunk were used as reference, along with an event marker. An activity classification algorithm was built based on a decision tree that incorporates rules inspired from movement biomechanics. The algorithm revealed excellent performance with respect to the reference system with an overall accuracy of 97% across all activities. The algorithm was also capable of recognizing all postural transitions and locomotion periods with elevation changes. Furthermore, the algorithm proved to be robust against small changes of tuning parameters. This instrumented shoe system is suitable for daily activity monitoring in elderly persons and can additionally provide gait parameters, which, combined with activity parameters, can supply useful clinical information regarding the mobility of elderly persons.

1. Introduction

Aging is frequently accompanied by loss of mobility, frailty, fear of falling and a greater risk of injury or disease caused by declining physiologic system dynamics [1]. It is crucial to remain active or become active again while aging, since suitable levels of physical activity (PA) can improve one's health and quality of life [2]. An increase in PA is linked to lower morbidity and mortality [3] by reducing the risk of cardiovascular diseases, stroke, dementia, diabetes and osteoporosis [4–6]. Consequently, a major focus in current geriatrics research is PA quantification in older adults and timely intervention delivery to preserve or improve mobility.

PA monitoring in older adults should provide information on activity behavior to be clinically useful. Therefore, the separation of sedentary periods, such as sitting or lying, from activity periods (standing and walking) is important. The evaluation can be improved if one can assess avoidance behavior e.g. using the elevator instead of climbing stairs. Finally, a detailed analysis of walking in terms of number of steps and gait velocity is essential in providing unique diagnostic and prognostic information [7].

Monitoring PA in daily life has seen major advances in recent years due to progresses in wearable technology, sensors miniaturization, and a boom of motion tracker devices and smartphone applications available on the market [8]. The focus of commercial devices is mainly on step counting or energy expenditure overview, rather than specific classification and quantification of activity type [9]. However, research studies have increasingly reported activity classification results and their importance in elderly participants [10–13].

Multi-sensor configurations appear to provide better results for activity classification but are more hindering during long term monitoring. This raises an important issue regarding sensor location: inertial sensors at the foot or tibia level could miss detecting sit-to-stand transitions, whereas sensors at the trunk level could misclassify stair locomotion [14]. Low accuracies were consistently reported for postural transition classification using single sensor locations in the aforementioned studies. While upper limbs provide useful information about body posture, a more

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accurate estimation of gait parameters can be obtained with lower limb sensors. The shank and the foot were shown to be excellent sensor positions for gait analysis in elderly subjects [15–17]. Considering this advantage, shoe-based sensors have been previously used to classify PA [18–21]. Several shoe-based systems for gait analysis and rehabilitation have been proposed in the literature [22–24], revealing major interest in this sub family of wearable sensors. This evidence strongly suggests employing shoe-based sensors to classify activities and to simultaneously provide specific gait analysis from a single body sensor location. However, none of the aforementioned concepts is currently outperforming the others in activity classification and daily life monitoring.

The present study aims to reduce the number of sensor locations while accurately recognizing activities in elderly users. Although several sensors were used, all were located only at the shoes. The system includes inertial and barometric pressure sensors, and an insole for foot pressure measurement. It was hypothesized that barometric pressure could inform about body elevation variations during locomotion and rest (e.g. level/incline, stairs locomotion, or elevators). Moreover we assumed that foot loading is related to posture (e.g. sitting, standing), and foot orientation may indicate the type of walking (e.g. level, ramp, or stairs).

2. Methods

2.1. Instrumented shoe system and reference system

The instrumented shoe system comprises the Physilog® (GaitUp, CH) including an inertial sensor (3D accelerometer, 3D gyroscope, 3D magnetometer), barometric sensor and the force sensing insole (IEE, LU), Fig. 1(a). Physilog® is thin (9.2 mm thickness) and light (<20 g) and includes a data logger. The insole has 8 sensors under the heel, arch, metatarsals, hallux and toes, sandwiched between two layers of neoprene, Fig. 1(b). The insole is powered by the Physilog® battery. The force data is amplified and digitized by custom-made converting electronics placed in a separate box, Fig. 1(a). An insole was placed inside each shoe, and a Physilog® module was strapped to the upper part of the shoe. The electronics box was strapped to the ankle.

For validation purposes, two additional Physilog modules were fixed to the right thigh and the trunk [25]. The reference classification algorithm proved concurrent validity with observation with both sensitivity and specificity for detection and classification of transitions and basic activity (siting, standing, walking) greater than 97%.

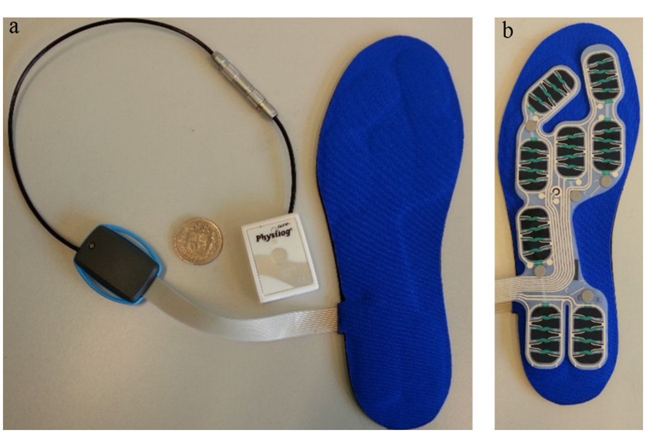

Fig. 1. Instrumented shoes system. (a) The Inertial Measurement Unit (IMU), force sensing insole and converting electronics (box with handles). (b) Force sensing insole with 8 sensors.

2.2. Data collection protocol

Ten elderly subjects (8 men, 2 women, age 65–75 years, weight 62–114 kg, height 162–184 cm) were recruited (convenient sample of community-dwelling older persons). Participants gave written consent to participate. The study was approved by the university's ethical committee: "Quantification of postural transitions using multimodal sensory input" under reference "EK 2012-N-32".

Each participant wore the instrumented shoes and the reference system. Data collection was carried out on campus at the university. A predefined track was followed by each participant, to mimic physical activities of daily life (~1 h of measurement per participant) and included level walking, sit-to-stand and stand-to-sit transfers, sitting and standing bouts, uphill/downhill and upstairs/downstairs walking, and elevator use.

Activities were carried out in a semi-structured protocol. Participants were free to perform all movements at their comfortable speed. An observer followed the participants and marked each period of stair climbing, elevator use, and uphill/downhill walking since these are not extracted from the reference algorithm, unlike sitting, standing, and level walking.

2.3. Activity classifier

2.3.1. Calibration

Data from all sensors were sampled at 200 Hz. Inertial sensors were calibrated in static position to remove offset and adjust gain [26], and to the foot-frame during a walking period of 10 steps by finding the gravitational axis when the foot was static and the medio-lateral axis during swing periods (by assuming that the movement is mainly in the sagittal plane) [16].

The insoles were calibrated to each participant's body weight (BW) during a 5 s period of static standing, by summing all sensors from both insoles and scaling the sum to the participant's weight. This is referred to as the total force (TF).

Pressure was converted to elevation by the barometric formula:

$$\text{elevation} = 44,330 \times \left(1 - \left(\frac{P}{P_0}\right)^{1/5.255}\right) \quad (1)$$

where P is the pressure measured by the barometer and P_0 is the static pressure at sea level. The elevation was low-pass filtered (Butterworth order 10 filter, 0.1 Hz cutoff) to remove high-frequency noise caused by gait and weather fluctuations that could mask an elevation change.

2.3.2. Biomechanics-inspired expert-based decision tree

The activity classification algorithm relies on expert-based rules inspired from movement biomechanics, Fig. 2. At each node, the data from one sensor are used to detect the activity at the node's output. First, the pitch angular velocity is used to distinguish locomotion from non-locomotion by performing step detection. Second, the estimated TF from the insoles is subjected to a threshold that separates sitting from standing. Third, the elevation obtained from the barometric pressure sensor allows the identification of activities with elevation change. Finally, the accelerometers are used to calculate the foot angle and distinguish between stairs and ramps climbing.

2.3.3. Locomotion/non-locomotion

The detection of locomotion relied on step detection based on toe off (TO) instant, the common event to all locomotion types. The TO was detected as a negative peak in the clockwise pitch angular velocity obtained from the gyroscope signal using wavelet approximation [17]. A gait cycle was defined as the time between