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Walking speed estimation using foot-mounted inertial sensors: Comparing machine learning and strap-down integration methods

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ABSTRACT

In this paper we implemented machine learning (ML) and strap-down integration (SDI) methods and analyzed them for their capability of estimating stride-by-stride walking speed. Walking speed was computed by dividing estimated stride length by stride time using data from a foot mounted inertial measurement unit. In SDI methods stride-by-stride walking speed estimation was driven by detecting gait events using a hidden Markov model (HMM) based method (HMM-based SDI); alternatively, a threshold-based gait event detector was investigated (threshold-based SDI). In the ML method a linear regression model was developed for stride length estimation. Whereas the gait event detectors were a priori fixed without training, the regression model was validated with leave-one-subject-out cross-validation. A subject-specific regression model calibration was also implemented to personalize the ML method.

Healthy adults performed over-ground walking trials at natural, slower-than-natural and faster-than-natural speeds. The ML method achieved a root mean square estimation error of 2.0% and 4.2%, with and without personalization, against 2.0% and 3.1% by HMM-based SDI and threshold-based SDI. In spite that the results achieved by the two approaches were similar, the ML method, as compared with SDI methods, presented lower intra-subject variability and higher inter-subject variability, which was reduced by personalization.

1. Introduction

Miniature solid-state inertial sensors are steadily gaining interest because of their low cost, limited power consumption, and the good user compliance when they are embedded in wearable sensor systems or portable devices. Hence, the application niches of these sensors extend beyond their traditional domains, e.g., automotive industry and factory automation, to include consumer and medical electronics. Currently, several applications in, e.g., human motion analysis [1,2], activity monitoring and classification [3,4], control of prosthetic devices [5,6] may benefit from integrating miniature solid-state inertial sensors within inertial measurement units (IMUs), with the research focus directed to developing advanced computational methods for data processing and information extraction.

One long-term goal of the research is to provide tools for assessing human subjects while they perform activities of daily living in unrestrained conditions. Walking is one of the most common human physical activities, with a prominent role in assessing the functional status of humans. Several methods of gait analysis have been studied and developed for estimating temporal and spatial gait parameters, such as stride time and length. Together with the gait parameters, walking speed can be associated with specific functional impairments and it is widely used to quantify improvements occurring after therapeutic and rehabilitative treatment [7,8]; moreover, walking speed is also instrumental to provide personal activity and localization information for applications in health care and pervasive computing [9,10].

Gait parameters can be estimated using miniature solid-state inertial sensors (accelerometers and gyros) in combination with a number of computational methods. As for the temporal parameters of gait, signal-based analysis and, to a more limited extent, methods of machine learning (ML) have been considered [11]. Usually, signal-based methods employ curve tracing to search for features occurring in sensor signals (e.g., by detection of local extremes or threshold crossings [12]); ML methods learn to recognize stable patterns that may recur in sensor signals due to the cyclical nature of gait [13]; as compared with signal-based methods, ML methods, such as adaptive logic networks and fuzzy logic, have been

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shown interesting results for their capability of accommodating the relatively large stride-to-stride variability observed especially in pathologic gait [5,6].

As for the spatial parameters of gait and walking speed, signal-based and model-based approaches have been considered [14,15]. Direct signal-based approaches apply strap-down integration (SDI) to inertial sensor data collected from selected anatomical points, such as the pelvis [16] and, more often, the foot [17–19] or the shank [20]. Depending on the configuration of the sensor system used for data collection, the position of the anatomical point relative to a ground-based reference frame has been estimated in the three-dimensional space [18,19] or the kinematic information has been restricted to the sagittal plane [20,21]. The main shortcoming of SDI lies in the time integration steps that are needed for pose estimation, which turn into unavoidable errors that tend to grow unbounded over time, unless a number of tricks are implemented [22]. Indirect signal-based approaches use either statistical regression with off-line parameter calibration [23] or training via artificial neural network [24–26]; usually, they have been based on data collected from inertial sensors that were placed on either the foot or close to the body center of mass (BCOM). Model-based approaches adopt biomechanical models of gait to explain the kinematics of walking and then to infer the variables of interest from signals that are measured using inertial sensors close to the BCOM [27–29].

Indirect signal-based and model-based approaches usually need model calibration procedures that are specific for each tested subject (personalization), which may even require additional sensing [30]. This is due to the limited generalization capabilities of the statistical model used for parameter estimation and to the effects of physiological variability on the accuracy of the biomechanical model. One distinctive advantage of statistical pattern recognition methods is indeed that rules can be learnt from signal features that do not require time integration of noisy and drifting signals. On the other hand, these methods would be critical in terms of generalization capabilities against inter-subject variability [31].

In this paper ML and SDI methods were compared for the estimation of normal-walking speed using inertial sensors, with particular regard to the issue of inter-subject variability. A generic ML method can perform poorly in situations when data from a monitored subject were not available at the time the method was trained. We outline that the generalization capabilities of ML methods (namely, how they deal with the problem of inter-subject variability) is perhaps the key point to be considered for boosting their use in human motion data analysis. This is the reason why we pursued the approach of leave-one-subject-out (LOSO) cross-validation.

We developed and tested various signal-based approaches, either direct or indirect, combining ML and SDI methods for estimating walking speed using foot inertial sensor data. A hidden Markov model (HMM) performed gait phase segmentation (loading response, mid stance, terminal stance and swing) using measurements of the medio-lateral component of the foot angular velocity. The SDI method used the HMM output to drive the computation of the linear acceleration, which was double-time integrated for stride length estimation (HMM-based SDI). In alternative to the HMM-based gait event detector, a standard threshold-based gait event detector using curve tracing was also tested, yielding the threshold-based SDI. The ML method used the HMM output and the linear acceleration estimated by the HMM-based SDI to estimate the stride length via linear regression. In the effort to improve generalization, the linear regression model was adapted by a subject-specific calibration procedure (personalization).

To evaluate the performance of the proposed methods, experimental results based on over-ground walking trials carried at different speeds by healthy subjects wearing an IMU-instrumented shoe are presented and discussed.

2. Materials and methods

2.1. Data acquisition and preprocessing

Data acquisition was performed using a device called WIMU (wearable inertial measurement unit), whose development is currently undergoing in our lab. The WIMU device is controlled by a 32-bit ARM Cortex processor (NXP Semiconductors LPC1768) and is powered using a 1.3 Ah lithium polymer battery. It is embedded with a bluetooth transceiver for connection to a host computer – an android smart-phone in the present configuration of the data acquisition system. An app on the smart-phone runs the graphical user interface for data logging; moreover, the app make a stopwatch tool available to the experimenter to perform the annotation of selected events during the experimental trials. WIMU devices integrate four sensing elements: a digital tri-axial gyro (InvenSense ITG-3200, with measurement range $\pm$ 2000°/s), a digital tri-axial accelerometer (Bosch BMA180, with measurement range $\pm$ 4 g, where g = 9.81 m/s^2 is the gravity acceleration), a digital tri-axial magnetic sensor (Honeywell HMC5843) and an air pressure sensor (Bosch BMP085). Angular rates and accelerations were sampled at 100 Hz and on-board digitally filtered using a Butterworth second-order low-pass filter (cutoff frequency: 10 Hz); magnetic and air pressure sensor data were not used in this work. Acquired inertial sensor data, logged into the ARM memory, were transmitted to the smart-phone before upload to a notebook for further processing using MATLAB.

Twenty-three healthy adults agreed to participate in the walking trials after being informed of the experimental procedures. Subjects were asked to walk along a 45-m corridor six times using their preferred shoes, twice for each of three walking speeds: free-selected (natural), slower-than-natural (slow) and faster-than-natural (fast) speeds – what slow and fast actually meant was left to the subjects themselves. A WIMU was tightly fixed to the shoelaces of the right feet at the foot instep, with one of the sensitivity axes approximately orientated in the medio-lateral direction, although no particular care was taken as for the WIMU alignment to the anatomical body planes. Before each walking experiment the accelerometer was calibrated by aligning its axes parallel and anti-parallel to gravity and the offset and sensitivity were adjusted accordingly [32]; the gyroscope was calibrated using a bias capture procedure at a time when the subjects stood still before starting walking: the angular velocity measured during walking was detrended by subtracting the mean of the gyro output taken over a rest period of 1 s.

Five waypoints (WPs) were marked along the corridor using adhesive tape at 0, 5, 35, 40 and 45 m distance from the starting point (Fig. 1).

Data acquired when subjects walked between the 5-m WP and the 40-m WP were retained for processing (steady-state walking); data between the 35-m WP and the 40-m WP were included in an ancillary dataset, which was used for selecting the feature set used by linear regression.

During each walking trial the experimenter annotated the times when the subjects' instrumented foot crossed the WPs (WP-crossing time stamps). One reason behind our choice to use manual annotation of WP crossing time stamps was that it would be helpful to assess walking activities in settings that are unstructured as much as possible. In fact, the use of external sensors to provide an automatic annotation of time stamps is in contrast with scenarios in which the algorithm can be personalized for the final user without the need of additional hardware. In previous studies a similar annotation approach was considered to get information on the number of steps [15] or on the amount of time needed to walk across a corridor [26].