Self-Calibration of Walking Speed Estimations Using Smartphone Sensors

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***Abstract*—Activity recognition for human behavior monitoring is an important research topic in the field of mHealth, especially for aspects of physical activity linked to fitness and disease progress, such as walking and walking speed. Sensors embedded into smartphones recently enabled new opportunities for non invasive activity and walking speed inference. In this paper, we propose a data fusion approach to the problem of physical activity recognition and walking speed estimation using smartphones. Our architecture combines different sensors to take into account practical issues arising in realistic settings, such as variability in phone location and orientation. Additionally, we introduce a novel automatic calibration methodology combining accelerometer and GPS data while walking in unconstrained settings, in order to reduce walking speed estimation error at the individual level. The proposed system was validated in 20 participants while performing sedentary, household, ambulatory and sport activities, in both indoor laboratory and outdoor self-paced settings. We show that by combining accelerometer and gyroscope data, smartphone location can be distinguished between the two most commonly used positions (*bag* and *pocket*), regardless of phone orientation (97% f-score). Location-specific activity recognition models can significantly improve activity recognition performance ($p = 0.0010 < \alpha$), especially helping in distinguishing activities involving similar motion patterns (91% f-score overall, improvements between 4% and 11% for *walking* and *biking* activities). Our proposed method to personalize walking speed estimates, by automatically calibrating walking speed estimation models during a short self-paced walk, reduced walking speed estimation error by 8.8% on average ($p = 0.0012 < \alpha$).**

I. INTRODUCTION

Activity recognition is an important research topic in the field of mHealth [1]. Mobile activity recognition can enable a series of applications for end users, from fitness tracking, health monitoring and context-aware services to home and work automation [2]. Because of the smartphone's small size, computational power, communication capabilities and their ubiquitous use in our society, they are an ideal platform for data mining applications, often replacing previous approaches based on body-worn wearable accelerometers [3]. To this aim, It has been shown in many studies that accelerometer and gyroscope data is capable of capturing basic activities [4], [5], making smartphones a suitable tool for continuous monitoring of user activities and behavior in terms of physical activity. Among the wide spectrum of physical activities, special attention is often put on walking and walking speed [6], [7], [8]. The ability to locate periods of walking, as well as walking speed, can be used for several applications. Walking speed is key in providing additional context when for example monitoring disease progress in different patient populations [9], as well as to measure physical performance in older populations [10]. Additionally, accurate walking speed estimation can be used to model physiological changes in different contexts and therefore provide accurate personalized energy expenditure estimations [11], cardiorespiratory fitness estimations [12] or automate gait based barometric authentications [13]. Walking speed estimation was often investigated considering walking periods only, recorded on a treadmill with the sensor or phone in a fixed position [6]. However, accurate detection of walking speed requires first to be able to detect walking periods at different phone carrying positions. Thus, providing reliable activity recognition is a necessary first step.

One of the main challenges when developing activity recognition and walking speed estimation systems is dealing with differences in persons' anthropometric characteristics, walking patterns, and possibly disease status, which cause difficulties in achieving high accuracy at the individual level. While anthropometric characteristics (e.g. height) have been used to extract subject-specific information about walking (e.g. stride length), or as input for machine learning-based models [6], no work so far investigated the possibility to use the rich multi sensorial information provided by smartphones, to personalize and dynamically recalibrate the walking speed models - without requiring user intervention. In this work, we propose a data fusion approach able to deal with both different phone locations and orientations to distinguish activities of daily living, as well as a personalization approach to walking speed estimation. In particular, our contribution is twofold:

1) We introduce a novel automatic calibration methodology in order to personalize walking speed estimates, reducing walking speed estimation error at the individual level. Our methodology combines accelerometer and GPS data while walking in unconstrained settings, to adapt subject independent estimates. Results show an improvement in walking speed estimation accuracy of 8.8% on average.
2) We tackle the problem of walking speed estimation in realistic settings by implementing phone location recognition and location-specific activity recognition models using orientation-independent features. We validated our algorithms on a datasets of 20 participants performing activities of daily living in the lab as well as in self-paced outdoor settings.

II. Related Work

A realistic approach to walking speed estimation using smartphones requires accurate activity recognition as a first step. For this reason we cover here related work on smartphone based activity recognition, before moving into walking speed estimation research and personalization approaches.

A. Phone Orientation and Location

Phone orientation was the first issue investigated by multiple authors [14], [15], [16], [17], [20], [21], [22]. As a matter of fact, even when the phone is carried always in the same location (e.g. bag or pocket), the orientation can change - since the smartphone is not fixed on the body - resulting in reduced activity recognition accuracy. The two main approaches reported in literature are: transforming the coordinates system before applying the classification algorithm [16], [19], or using orientation-independent features [17], [20], [22]. Orientation-independent features are calculated summing or squaring the accelerometer signal over the three axis, after removing the static component due to gravity [20]. On the other hand, transforming the coordinate system relies on the hypothesis that all input accelerometer signals can be transformed into the same global reference system, on which a classifier was trained. This approach showed improvement in performance up to 20% compared to when no orientation adjustment was performed. However, typically the transformation is performed on data retrieved using the phone in a *fixed* different orientation [16], while the phone can change orientation *continuously* when carried - for example - in a bag. Thus, the orientation-independent features seem to be a more robust approach to practical activity recognition in real life.

A second major issue is phone location, which is not fixed on the body. Pioneering work on this matter was done by Kunze et al. [23], who investigated the possibility to determine on-body sensor position based on accelerometer data while walking. Different approaches were investigated using mobile phones, from location-independent models robust to changes in location, to location-specific models trained on the most commonly used locations [24]. Solving the location issue typically requires a different approach compared to the ones used to tackle variability in orientation. In [16], the authors showed that even when applying a transformation to the coordinates system, different on-body locations require different classifiers to perform optimally. Early work focused on locating the phone without investigating the impact on activity recognition accuracy [14], [15], [25]. However, due to the high variability in phone orientation and movement in general, none of these works includes the *bag* as a *location*, even though literature reports it as the most commonly used location together with the *pocket* [24]. Recent work by Henpraserttae et al. [16] showed that location-specific models can improve performance of the activity recognition models, but the author did not propose an automatic way to determine phone location. Finally, the work by Kelly and Caulfield [18] introduced phone location classification, showing performance improvement of 9.2% precision and 6.2% recall. However, the proposed model is validated on a few subjects and during walking only. Additionally, the authors did not include the *bag* either, limiting the impact of dynamic changes in orientation on the classification process.

B. Walking Speed Estimation using Smartphones

Walking speed estimation methods based on wearable sensors can be classified into two categories: machine learning-based methods [6], [11], [26] and kinematic models [27]. When using a single sensor, especially an unconstrained smartphone, employing kinematic models is not feasible due to lack of information on the limbs orientation and position over time. However, machine learning approaches can capture the relation between the sensors' features and speed, beyond an explicit kinematic model. Most previous work that applies machine learning methods to walking speed estimation assumes that there are one or more accelerometers at fixed positions on the body [8]. However, when using a smartphone, walking speed estimation suffers from all of the above mentioned problems: reduced accuracy was reported when varying both phone location and orientation [28]. Additionally, walking speed estimation models suffer from additional limitations. Not only the models are often developed considering a single location and orientation, with the phone fixed on the body, but protocols include walking periods only [6]. However, accurate detection of walking speed requires first to be able to detect walking periods, regardless of phone location and orientation. Even when the phone location and orientation issues were taken into account, the system was validated on a very small number of subjects and activities [7], limiting the practical applicability of such systems.

C. Personalization of Smartphone based Models

Recent work by Weiss and Lockhart [29] compared activity recognition accuracy when using subject independent and dependent data, showing significant increases in performance when using the latter. Similar results can be obtained when developing walking speed models. While it is clear that including personal data in the models improves accuracy of activity recognition and walking speed estimation, practical approaches aiming at providing such personalized data are still lacking. Longstaff et al. [30] investigated both active and semi-supervised learning to include personal data in the activity recognition models. The authors showed improvement in performances for poor classifiers of about 6-8%. Some of these methods are limited by the need of user interaction to provide personal data (e.g. active learning). Active-learning, for example, requires the user to label personal data from time to time, but while it is rather straightforward to provide input about activity type, we are typically unaware of the speed we are walking at. Thus, we propose to personalize the models in a different way, exploiting the sensory-rich information which can be derived from todays' smartphones. While other methods aim at using one or more pre-trained classifiers to label new data, and re-train such classifiers (e.g. co-training), our approach aims at automatically gathering new reference data for a specific user using the phone's sensors (i.e. GPS), and re-calibrate walking speed models trained independently of the subject.

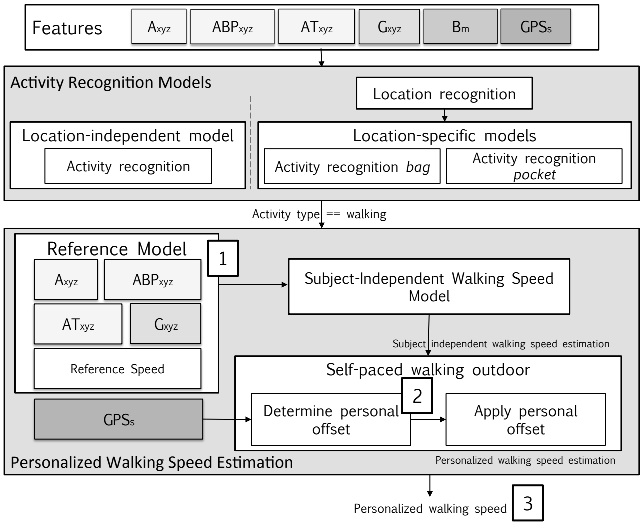

Fig. 1. Block diagram of the activity recognition and personalized walking speed estimation system architecture. For activity recognition, we implemented location-independent models as well as location recognition+location-specific models. Different subsets of the smartphone's sensors are used for both location recognition and activity type recognition. The walking speed estimation system architecture is divided into three main parts; 1) Subject-independent models are built using treadmill reference data. 2) GPS data during a self-paced walk outdoor is used to determine the offset with respect to the subject-independent walking speed estimation. Finally, 3) the offset is applied to personalize walking speed estimation for a certain person.

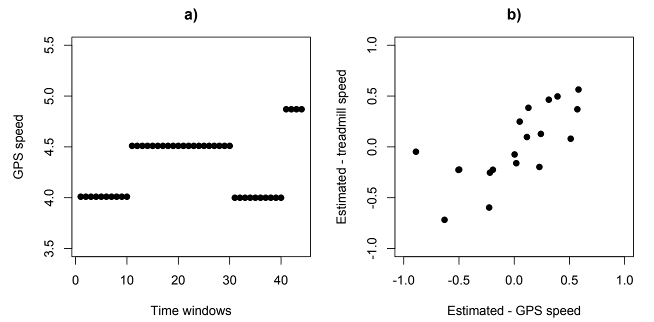

Fig. 2. a) Example of recorded GPS data, showing the low resolution of the signal, which jumps by 0.5 or 1 km/h between consecutive data points. b) Positive correlation between differences in estimated walking speed (from subject independent models) and GPS data, and differences in estimated walking speed and reference treadmill data.

III. Analysis Approach and Methodology

This section covers the approach we used to analyze the role of different sensors and features for the implemented models. A block diagram of the system architecture is shown in Fig. 1. In order to provide reliable walking speed estimation using smartphones, we first investigated role of accelerometer (un-filtered, band passed filtered and transformed with respect to the coordinate systems), gyroscope and barometer sensors for phone location recognition and activity type recognition using either location-independent or location-specific models. Based on the activity recognition models recognizing the walking activity, we performed the walking speed estimation task. Then, we introduce a methodology combining multiple smartphone's sensors to automatically personalize walking speed estimates, by acquiring new reference during a self-paced outdoor walk.

A. Activity Recognition

For location-specific modeling, we considered two phone wearing locations (*bag* and *pocket*), since these two locations are reported as the most commonly used [24]. Device orientation was not controlled, leaving freedom to the participants to put the phone in their *bag* or *pocket* in any orientation. Since data recording was manually started before each activity, variability in orientation was even higher, allowing the participants to change orientation between different activities. The activity recognition analysis focuses on three aspects related to the smartphone's sensors, orientation and location:

1) To determine which accelerometer features are most robust to sensor orientation variability: accelerometer features (ACC_{xyz}) were divided into three groups. The first group comprises un-filtered features - i.e. features including the effect of gravity - referred to as A_{xyz}. The second group includes band passed features only - i.e. features where the static component due to gravity has been removed (ABP_{xyz}). Finally, the third group of features refers to features transformed with respect to the coordinate system, AT_{xyz}. The most discriminative feature set is used for further analysis.

2) To assess which smartphone's sensors are most useful in discriminating between activity classes: on top of accelerometer features, we included gyroscope (G_{xyz}) and barometer (B_m) data to determine the impact of such sensors in both phone location recognition and activity type recognition.

3) To assess the importance of smartphone location for the activity recognition task: location-independent models as well as combinations of location recognition + *location-specific* models were implemented to evaluate the impact of phone location recognition when rich multi sensor information is combined, as well as the impact of phone location *misclassification* on the overall activity recognition accuracy (see Fig. 1).

B. Personalized Walking Speed Estimation

GPS data can provide speed information during outdoor self-paced walking, thus providing reference speed together with acceleration, without the need for a treadmill or laboratory test. Therefore, we hypothesized that GPS speed data (GPS_s) during a short, self-paced outdoor walk could be used to re-calibrate and personalize subject-independent walking speed models developed using treadmill data at the gym. Our assumption is based on the fact that Considering that the GPS signal acquired with smartphones is often inaccurate and provides low resolution (see Fig. 2 a), we used it to determine under and overestimations of the subject independent walking speed models, and not the actual difference between the models. More specifically, our approach is divided into three steps (see Fig. 1). As commonly reported, we first 1) developed subject-independent models using the smartphone's data as well as treadmill-derived reference speed (multiple linear regression models). Secondly, 2) we collected data during a short self-paced walk outdoor, and used this data to determine under or over-estimations of the subject-independent walking speed model for a specific person. Finally 3), the walking speed estimate is adapted (applying a person-specific offset) based on possible under or over-estimations of the subject-independent model. Fig. 2 b) highlights the feasibility of this approach. Even though GPS data is low resolution, there is a consistent positive correlation between differences in estimated walking speed (from subject independent models) and GPS data, and differences in estimated walking speed and reference treadmill data ($p = 0.0012 < \alpha$). Thus, GPS data points out if the subject independent models is under or over-estimating walking speed for a certain person.

IV. Implementation

A. Features

Features were used to derive location recognition, activity recognition and walking speed estimation models. Location recognition was performed to classify between the *bag* and *pocket* locations. Activity recognition was performed to classify the seven clusters of activities introduced in Table I, independently of the smartphone orientation. For location and activity recognition models we used only time-domain features to limit the computational complexity and ease future embedded implementations of the proposed algorithms, since these algorithms should run continuously. Table II lists all features and the sensors from which they were derived. Accelerometer data from the three axes was either used without filtering (A_{xyz}), band passed filtered (ABP_{xyz}) to remove the static component due to gravity - reducing orientation-dependance - or transformed with respect to the coordinate system (AT_{xyz}), as proposed in literature. Barometer signals were computed over windows of 8 seconds instead of 4, while GPS speed was determined buffering the most recent data points reported by the smartphone as highly accurate. GPS speed during walking was discarded if below 2.5 km/h or above 6 km/h. The importance of different features for the location and activity recognition tasks was investigated by selecting only subsets of the features listed in Table II. In particular, we first analyzed which accelerometer feature set was most discriminative, among A_{xyz}, ABP_{xyz} and AT_{xyz}. Then, the most discriminant accelerometer-only feature set was extended with gyroscope (G_{xyz}) and barometer (B_m) data to analyze the impact of such sensors and features on classification accuracy.

In addition to accelerometer and gyroscope time-domain features, we extracted frequency-domain features for walking speed estimation models. These models should run for periods of time significantly lower compared to the location and activity recognition systems, thus allowing for more computational power. In particular, we extracted signal power and frequency peaks of the accelerometer signal.

B. Smartphone Location Recognition

We adopted a constant set of parameters for the classifier type of the location recognition system and varied the features used in order to understand what is the contribution of different sensors in determining smartphone location. We selected a time window of 4 seconds, which is short enough to detect short breaks in sedentary time, and long enough to capture the repetitive patterns of some activities (e.g. walking or running), except for the barometer data, which was calculated over the last 8 seconds of data to provide a more robust signal. Given the positive results in past research on activity recognition, we selected Support Vector Machines (SVMs) as classifiers. For the SVMs, we used a polynomial kernel with degree 5 ($\lambda = 10, C = 1$).

TABLE I. Distribution of the activities into the seven clusters used for activity recognition.

Cluster name	Original activities
Sedentary	sitting, standing
Household	kitchen work (washing dishes)
Walking	walking on a treadmill at 2.5, 3, 3.5, 4, 4.5, 5, 5.5 and 6 km/h, walking at 3 km/h and 5% inclination, walking at 3 km/h and 10% inclination, walking outdoor self-paced
Walking upstairs	walking three flights of stairs, upstairs
Walking downstairs	walking three flights of stairs, downstairs
Biking	biking outdoor self-paced
Running	running on a treadmill at 7 km/h

TABLE II. Sensors and features used for phone location recognition, activity recognition and walking speed estimation models.

Sensor	Features
Accelerometer	A_{xyz}: mean and standard deviation of the signal, ABP_{xyz}: mean squared signal, interquartile range of the signal, AT_{xyz}: mean squared signal, interquartile range of the signal, mean and standard deviation of the signal
Gyroscope	G_{xyz}: mean squared signal, interquartile range of the signal, mean and standard deviation of the signal
Barometer	B_m: altitude difference in meters
GPS	GPS_s: speed

C. Activity Type Recognition

Activities listed in Section V were grouped into clusters to be used for activity recognition. See Table I for a list of the activities and clusters. As for the location recognition models, we adopted a constant set of parameters for the classifier type of the activity recognition system and varied the features used in order to understand what is the contribution of different sensors in determining the activity performed by the smartphone carrier. For each combination of features used, we implemented a *single* activity recognition model, as well as *location-specific* activity recognition models using only data collected in the *bag* or *pocket* location. For all classifiers we selected a time window of 4 seconds, except for the barometer data, which was calculated over the last 8 seconds of data to provide a more robust signal. We selected Support Vector Machines (SVMs) as classifiers. For the SVMs, we used a polynomial kernel with degree 5 ($\lambda = 10, C = 1$). Additionally, we down sampled our dataset during model development, to avoid training poor classifiers due to a imbalanced dataset with predominantly walking data. Even though the classifiers were trained with less data, validation is performed using all data from the left-out subjects (see Section V).

D. Personalized Walking Speed Estimation

The personalized walking speed estimation methodology introduced in this paper (see Section III for details) relies on subject-independent walking speed estimation models. The walking speed estimation models were implemented as multiple linear regression models which predict walking speed using as features the individual's height and the accelerometer and gyroscope features listed in Table II, plus the additional frequency-domain features.

Given the poor resolution of the GPS signal (see Figure 2 a), we did not rely on the actual difference between the estimated and GPS speeds to correct the subject-independent walking speed estimation. On the other hand, after calculating the difference between the estimated walking speed and the GPS speeds for each participant, we determined the actual person-specific offset to apply - as percentage of the actual difference -, according to two criteria: 1) we analyzed the performance of the personalized walking speed estimation in terms of average reduction in RMSE over all participants, 2) we analyzed individual errors for participants for which the proposed methodology did not provide error reduction.

Personalized walking speed estimation ($PerW_{speed}$) can be derived as follows: $PerW_{speed} = SubjIndW_{Speed} + offset$, Where $offset = coeff * Speed_{diff}$. $SubjIndW_{Speed}$ is the subject independent walking speed estimate, $coeff$ is the main parameter to be determined and $Speed_{diff}$ is the speed difference between the estimated subject-independent walking speed and the GPS speed during a self-paced short walk outdoor.

V. Evaluation Study

The dataset acquired in this work contains more than 26 hours of annotated data from 20 participants, consisting of reference activity type, phone location, three axial acceleration, three axial gyroscope, barometer and GPS data acquired from a Google Nexus 4 smartphone.

A. Participants

Participants were twenty (14 male, 6 female) self-reported healthy students or employees at Eindhoven University of Technology. Mean age was 29.4 ± 5.1 years, mean weight was 70.2 ± 9.9 kg, mean height was 1.76 ± 0.10 m and mean BMI was $22.52 \pm 1.93\, kg/m^2$.

B. Experiment Design

Participants reported at the lab after being instructed on the study protocol by the experimenter. The recordings consisted of two sessions, a treadmill session at the gym and a free-living session carried out both in a home-like setup and outdoor. The gym session consisted mainly of walking, including the following activities: *walking at 2.5, 3, 3.5, 4, 4.5, 5, 5.5 and 6 km/h, walking at 3 km/h, 5% inclination, walking at 3 km/h, 10% inclination, running at 7 km/h*. The indoor part of the second session consisted in: *walking upstairs, walking downstairs, kitchen activities (e.g. washing the dishes) and sedentary behavior (e.g. sitting and standing)*. Finally, the outdoor part of the second session included: *walking self-paced and biking self-paced*. All activities lasted between 1 and 10 minutes, and were repeated twice by all participants in order to collect data for both the *pocket* and *bag* locations. Before each activity the participants were asked to place the smartphone in the pocket or bag in any random orientation, without pre-defined positions or instructions.

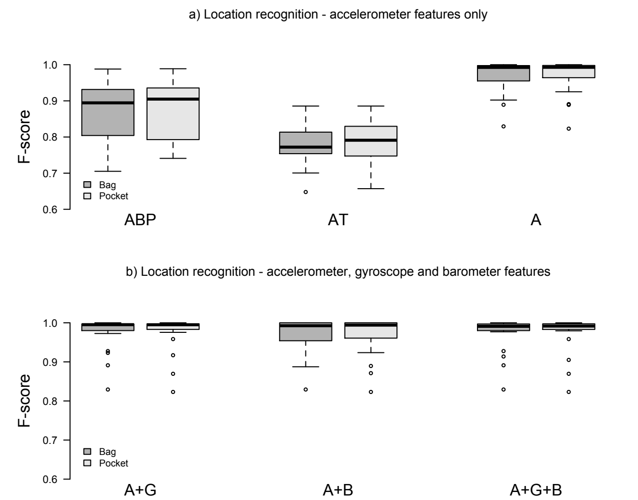

Fig. 3. F-score for the smartphone location recognition classifier, bag and pocket classes. a) Results obtained with different sets of accelerometer features, b) Combination of the best accelerometer features (A) with gyroscope and barometer features.

C. Statistics and Performance Measures

Models were evaluated using leave-one-subject-out evaluation. Performance of the activity recognition models was evaluated using the F-score, thus combining precision and recall for each cluster of activities. The F-score was used to provide a fair comparison given the unbalanced dataset collected, where walking activities are predominant. Results for walking speed estimates are reported in terms of Root Mean Square Error (RMSE). Paired t-tests were used to compare the F-score or RMSE between different models. Significance was assessed at $\alpha < 0.05$.

VI. Results

A. Smartphone Location Recognition

Smartphone location recognition F-score was 0.87 when using band passed accelerometer features (ABP), 0.77 when using transformed features (AT) and 0.96 when using unfiltered accelerometer features (A).Including gyroscope features (G) significantly improved results ($p = 0.04 < \alpha$, F-score $= 0.97$). Recognition rates were similar for the bag and pocket smartphone locations (see Fig. 3).

B. Activity Type Recognition

Activity recognition performance was significantly improved when using a multi-sensor approach, with the barometer being the most effective sensor due to the impact on recognizing walking upstairs and downstairs activities. Overall, activity recognition F-score for *location-independent models* (see Fig. 4) ranged between 0.49 and 0.64 when accelerometer data only was used. F-score increased to 0.65 when including gyroscope data and to 0.89 when including barometer data. Activity recognition F-score for *location-specific models*, including the effect of misclassification, ranged between 0.49 and 0.67 when accelerometer data only was used. F-score increased to 0.70 when including gyroscope data and to 0.91 when including barometer data (see Fig. 6).

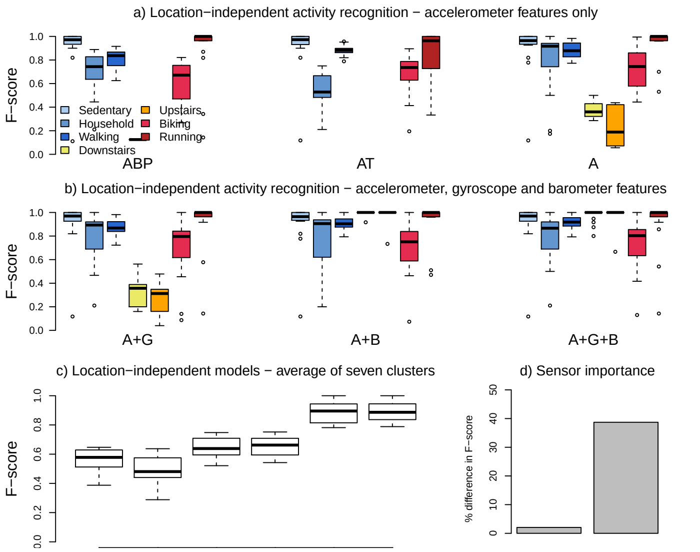

Fig. 4. F-score for the single activity recognition models. a) Results obtained with different sets of accelerometer features, b) Combination of the best accelerometer features (A) with gyroscope and barometer features. c) Average F-score for all clusters of activities, d) Importance of single sensors when used on top of the accelerometer data (% difference in F-score).

Performance reduction between models assuming perfect smartphone location recognition and models including misclassification error reached 53% for accelerometer-only models, and decreased to less than 1% for models combining accelerometer, gyroscope and barometer data (reduced misclassification effect). Activity recognition for location-specific models was significantly better compared to location-independent models (p=0.0010, 2% F-score increase). Differences were between 0 and 11% for the seven clusters of activities. The highest improvements in location-specific models were reported for activities where barometer features could not discriminate more than accelerometer-only features, for example walking and biking activities (F-score difference between 4 and 11%).

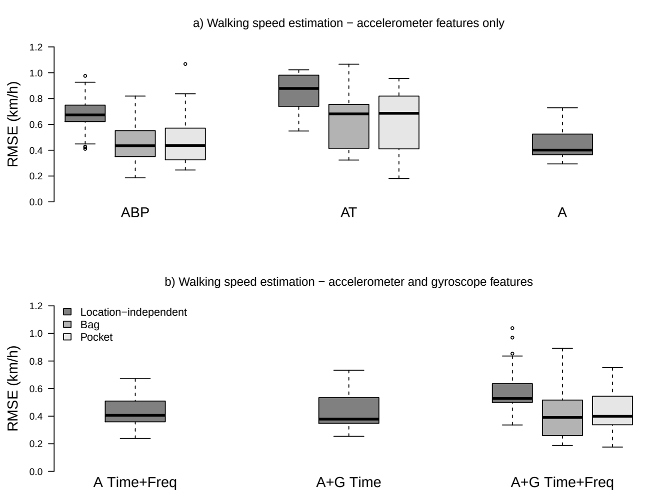

Fig. 5. RMSE for single and location-specific walking speed models. a) Results obtained with different sets of time-domain accelerometer features, while plot b) shows the combination of the best time-domain accelerometer features (A) with gyroscope and and frequency-domain accelerometer features.

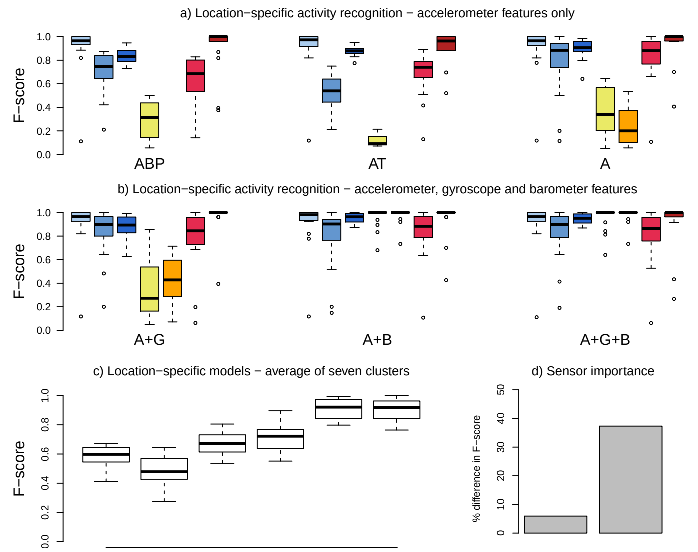

Fig. 6. F-score for the location-specific activity recognition models. All results include the impact of smartphone location misclassification (i.e. applying the wrong location-specific model). a) Results obtained with different sets of accelerometer features, b) Combination of the best accelerometer features (A) with gyroscope and barometer features, c) Average F-score for all clusters of activities, d) Importance of single sensors when used on top of the accelerometer data (% difference in F-score).

C. *Personalized Walking Speed Estimation*

After calculating the difference between the estimated and GPS speeds for each participant, we determined the actual person-specific offset to apply - as percentage of the actual difference -, according to two criteria: $1)$ we analyzed the performance of the personalized walking speed estimation in terms of average reduction in RMSE over all participants, $2)$ we analyzed individual errors for participants for which the proposed methodology did not provide error reduction.

Figure 7 $a)$ shows that RMSE can be reduced by up to 12.4% when 45% of the difference between the subject-independent estimated speed and the GPS speed is used as the offset to personalize walking speed estimation (average of bag and pocket models). However, such error reduction penalizes some individuals, for which the proposed normalization does not work as expected. Figure 7 $b)$ shows the percentage error (maximum and average) for such subjects. Since our aim is to improve walking speed estimation error at the individual level, there is a trade-off between overall RMSE reduction (Fig. 7.a) and individual error for those subjects for which the methodology does not perform optimally (Fig. 7.b). Taking into account these criteria we chose 25% as the optimal coefficient (indicated as % difference between estimated and GPS speed in Fig. 7 a)) to calculate the offset. Correlation between the predicted walking speed during the outdoor self-paced walk with the phone in the pocket and the predicted walking speed during the outdoor self-paced walk with the phone in the bag, computed for all subjects, was significant ($p = 0.045 < \alpha$), satisfying the assumption that persons walk self-paced at approximately a constant personal speed. RMSE for location-specific walking speed models was lower than for location-independent models regardless of the features used (see Fig. 5). Error reduction were between 25 and 39% (from

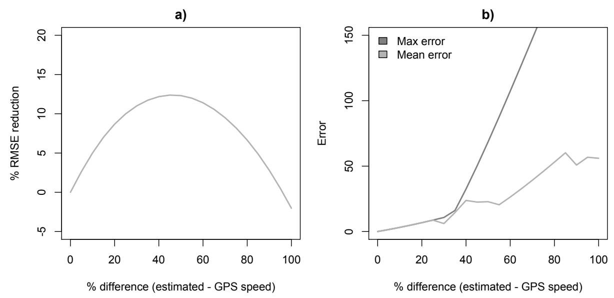

Fig. 7. Trade-offs between overall and individual accuracy of the personalization methodology. a) RMSE percentage reduction (average of bag and pocket models for all subjects) when applying different offsets to calculate personalized walking speed. b) Maximal and mean individual error for those subjects for which the methodology does not perform optimally, in relation to the different offsets applied to calculate personalized walking speed.

0.73 km/h to 0.43 km/h for the best accelerometer-only model). Gyroscope features as well as frequency-domain features did not significantly reduce error ($p = 0.367 > \alpha$). RMSE was reduced by 8.8% when personalizing the walking speed estimation according to the proposed methodology ($p = 0.0012 < \alpha$, from 0.43 to 0.39 km/h), see Fig. 8.

VII. Discussion

In this work, we proposed a method to personalize walking speed estimates combining multiple smartphone sensors. Our aim was to develop models and algorithms able to provide walking speed estimates both accurate at the individual level and realistic in free-living conditions. To achieve our goal, we covered a wide set of topics, ranging from sensor location and orientation for activity recognition, to data fusion of multiple sensors and personalization techniques merging such sensors' data. Most importantly, we validated our algorithms on an extensive datasets of 20 participants performing activities of daily living in the lab as well as in self-paced outdoor settings, allowing participants to place the smartphone in the two most commonly used locations (bag and pocket [24]), and in random orientations. In this section we discuss the main findings and results, with respect to the points highlighted in Section III. We start discussing practical aspects, such as activity recognition and the phone location and orientation issues, then move to personalized walking speed estimations.

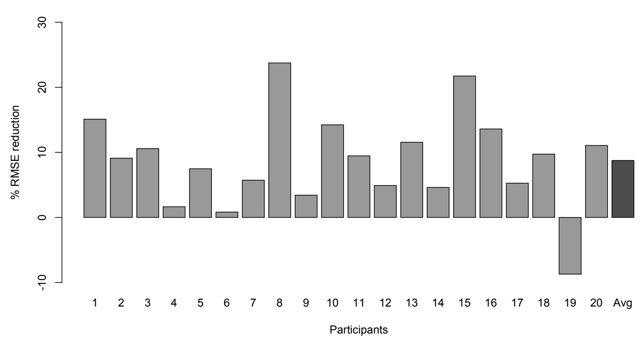

Fig. 8. Percentage reduction in RMSE (km/h) when personalizing the walking speed estimation according to the proposed methodology. RMSE is decreased for all subjects but one, average is 8.8%.

A. Activity Recognition

In the presented analysis, we made the following findings:

1) To determine which accelerometer features are most robust to sensor orientation variability: according to our analysis (Fig. 3, 4 and 6), both location recognition and activity recognition performance improved when using unfiltered accelerometer features (A_{xyz}). While previous research tried to reduce variability in orientation by either using orientation-independent features (e.g. our ABP_{xyz} set), or by transforming the accelerometer signal with respect to the reference coordinate system (i.e. the AT_{xyz} feature set), we did not find improvement in performance when applying such techniques. We believe both strategies are affected by practical limitations sometime excluded by some of the previous works. For example, when the phone is fixed in a certain position on the body, transformed accelerometer features (AT_{xyz}) can most likely reduce error due to orientation variability. However, most of the time the phone orientation is continuously changing (e.g. when the phone is moving inside a bag).

2) To assess which smartphone's sensors are most useful in discriminating between activity classes: our results show accelerometer and barometer as the main contributors to accurate activity type recognition. While gyroscope data was found useful in discriminating phone location ($p = 0.04 < \alpha$, F-score $= 0.97$) - together with accelerometer data - probably due to the swinging pattern peculiar of carrying the phone in a pocket, compared to the more random movement when the phone is in a bag, the impact on activity recognition was minimal (see Fig. 4 and 6). We speculate the scarce impact of gyroscope data for the activity recognition task is mainly due to the poor information that can be extracted from such sensors when the phone is loosely connected to the body. In different situations, for example when a wearable sensor is placed on the body, improvements in accuracy are often reported.

3) To assess the importance of smartphone location for the activity recognition task: location-specific activity recognition models outperformed location-independent models ($p = 0.0010 < \alpha$). Feasibility of location-specific models is confirmed by the high accuracy of the phone location recognition model, whose misclassification causes a decrease in F-score of less than 1%. The overall increase in F-score when using location-specific models was 2%, due to the fact that integrating multiple sensors can provide accurate activity recognition for certain clusters of activities, regardless of phone location and orientation (e.g. including barometer data to detect walking upstairs and downstairs). However, for activities involving similar and irregular motion (e.g. walking or biking while carrying the phone in a bag), improvements ranged between 4 and 11%, showing the importance of location-specific models for accurate physical activity monitoring using a smartphone in unconstrained settings.

B. Personalized Walking Speed Estimation

We introduced a novel methodology to reduce walking speed estimation error at the individual level. Our hypothesis was that GPS data during a short self-paced walk could be used to determine the performance of subject-independent walking speed models on a specific person, and adapt such estimate to better fit the person. The feasibility of our methodology was confirmed when computing the correlation between treadmill data and self-paced walking data. The difference between the speed measured by the treadmill and the subject-independent speed estimated by the model was positively correlated with the difference between the speed measured by the GPS and the subject-independent speed estimated by the model. However, the inaccuracy of the GPS signal, and especially the low resolution (0.5-1km/h), prevented us to use the actual difference between the estimated speed and the GPS speed as offset to adapt the estimate at the individual level. Analyzing different coefficients (% of offset to be used to personalize the estimate), we found the range between 25 and 40% to be optimal to reduce RMSE. Better hardware might allow for a different approach, where the actual difference in speed could be used to personalize the estimate instead of only a percentage of it. However, the methodology would still hold. For the task of walking speed estimation, standard personalization techniques typically used for activity recognition cannot be used. Active-learning, for example, requires the user to label personal data from time to time, but while it is rather straightforward to provide input about activity type, we are typically unaware of the speed we are walking at. Thus, we proposed a different approach, based on automatically integrating multiple sensors available in any smartphone, to personalize the estimate at the individual level by acquiring new reference data during a short walk outside.

C. Limitations

We recognize limitations in our work. Even though we took care of limiting the computational complexity of our system, by using only time-domain features for location and activity recognition models, we did not implement our models on a smartphone yet. Secondly, our methodology to personalize walking speed requires GPS data, which increases power consumption significantly. While literature already showed that energy-efficient activity recognition on mobile devices is feasible, [31], an adaptive sampling technique able to determine when the user is walking outside should be implemented for practical usability of the proposed solution. However, offline processing is a natural first step when validating new techniques and methodologies.

Another limitation of our work is due to the limited locations and orientations adopted during data collection. We choose the two most commonly reported locations (i.e. bag and pocket), and introduced variability by letting the participants place the phone in their left or right pocket and without predefined instructions on phone orientation. Also, participants were asked to reposition the phone between different activities, in order to introduce even more variability in phone orientation. However, our approach is not extensive of all the locations where a phone can be carried, and the validity of the proposed models should be validated in different settings.

VIII. Conclusions

In this paper, we proposed a personalization approach to walking speed estimation. In order to build models robust to free living settings, we investigated different phone locations and orientations to distinguish activities of daily living. Location-specific activity recognition models could significantly improve activity recognition performance. The activities to benefit the most from this approach were the ones involving similar motion patterns, such as *walking* or biking with the phone in a bag. This finding highlights the importance of this approach for walking speed estimation. Our proposed methodology for personalizing subject-independent walking speed estimation models used data during a short self-paced walk outdoor, and could reduce walking speed estimation error by 8.8% on average, by combining accelerometer and GPS information. Overall, we conclude that practical walking speed estimation monitoring using a smartphone is feasible.

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