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Using barometric pressure data to recognize vertical displacement activities on smartphones

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ABSTRACT

We introduce a novel, efficient methodology for the automatic recognition of major vertical displacements in human activities. It is based exclusively on barometric pressure measured by sensors commonly available on smartphones and tablets. We evaluate various algorithms to distinguish dynamic activities, identifying four different categories: standing/walking on the same floor, climbing stairs, riding an elevator and riding a cable-car. Activities are classified using standard deviation and slope of barometric pressure. We leverage three different inference models to predict the action performed by a user, namely: Bayesian networks, decision trees, and recurrent neural networks. We find that the best results are achieved with a recurrent neural network (reaching an overall error rate of less than 1%). We also show that decision tree classifiers can achieve good accuracy and offer a better trade-off between computational overhead and energy consumption; therefore, they are good candidates for smartphone implementations. As a proof of concept, we integrate the decision tree classifier in an App that infers user activity and measures elevation differences. Test results with various users show an average recognition accuracy rate of about 95%. We further show the power consumption of running barometric pressure measurements and analyse the correlation of pressure with environmental factors. Finally, we compare our approach to other standard methodologies for activity detection based on accelerometer and/or on GPS data. Our results show that our technique achieves similar accuracy while offering superior energy efficiency, independence from the sensor location, and immunity to environmental factors (e.g., weather conditions, air handlers).

1. Introduction

In the last decades, smartphones became the central computer and communication device in people's activities and lives. Current smartphones includes a variety of sensors that can be used for the continuous real-time location-aware monitoring of human activities as well as environmental conditions [1]. This has opened for research that ranged from very sensitive health applications [2] or privacy-concerned proximity solutions [3] up to leisure purposes [4]. Also, exploiting the multiplicity of mobile devices for large collection of measurements is beneficial to multiple fields, from health [5] to smart-cities [6]. Boosted up by smartphone computing and communication, activity recognition is spreading and developing: more and more applications rely on the knowledge of or on the distinction among human activities. Detecting the action a subject is performing can serve many purposes, for example, monitoring a variety of pathological conditions [7], or sending alerts when a potentially dangerous activity is sensed [8], or identifying lifestyle quality [9,10]. Collected information can be valuable for suggesting countermeasures (e.g., stimulating physical activity if a sedentary lifestyle is recognized). Other information, as location, can be inferred (e.g., detecting floor transitions when a subject passes from climbing stairs to standing still [11]). A major challenge in designing an activity recognition system is the user acceptance. If a system invades the private sphere, the user might be reluctant to adopt it. With the rise of the smartphones, a large part of the activity recognition research switched towards wireless sensor measuring with mobile phones [12]. Smartphones have the double advantage of both being equipped with multiple sensors, and being an ubiquitous commercial product. Latest generation of devices are indeed equipped with a rich set of sensors, including accelerometer, barometric pressure sensor, compass, gyroscope, proximity sensor, light sensor, GPS, microphone, and camera. The key capabilities of sensing, computing and communicating are integrated in the universally accepted and always-with-you smartphone [1,13]. For these reasons, the detection of user activities using sensors embedded in a smartphone is gaining a momentum. Traditional methods for tracking activities with

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smartphones mainly rely on integrated accelerometer sensors. However, the difference in the way of performing a well defined activity and of carrying the device, even for the same user, can lead to a very poor accuracy [14]. A drawback of the accelerometer sensor is energy consumption, which (if always on) is significant [15] and is mostly determined by the need of keeping the phone's components active to access sensors results [16]. Emerging methodologies aim at applying multi-sensor data fusion techniques, taking advantage of the abundance of sensors embedded in smartphones and their complementarity [17,18]. Of course, the use of multiple sensors negatively impacts energy consumption. At present, the two major challenges in the accomplishment of good activity detection with smartphones are still energy efficiency and independence from the device's position along human body. In the present work, we define a new class of activities - Vertical Displacement Activities (VDAs) - where major movement is along the vertical axis. Examples of VDAs can be standing, climbing stairs, riding a cable-car, riding an elevator, or jumping. Our methodology shows that it is possible to identify VDAs with very good accuracy relying only on barometric pressure sensors available on off the-shelf smartphones [11]. Barometric pressure sensors have been traditionally used for height estimation by measuring pressure changes [19]. Information derived from accelerometer data and GPS based localization services can be integrated in a second step, only if really needed. Pressure sensing can provide, for example, complementary information to pedestrian dead reckoning. The main advantage is that switching from a sensor to another can extend battery life and optimize the detection analysis. Moreover pressure measurements are totally independent of the phone position.

Our paper is structured as follows. We firstly discuss the literature (Section 2) and the rationale of our work (Section 3). In Section 4 we present our experiments for investigating the characteristics of barometric pressure in different scenarios. We defined four different user dynamics mode (“standing/walking” on the same floor, “climbing stairs”, “riding a cable-car”, and “riding an elevator”). Then we collected training labelled data on barometric pressure in the corresponding scenarios. We tested three different inference methods to classify trained data. The metric used to choose the best model is a good trade-off between performance and costs. It is widely known that recurrent neural networks are the state of the art in inference models, however their implementation in resource-constrained devices (i.e. smartphones) presents several issues due to their computational needs and their impact on battery lifetime. On the other hand, decision trees and Bayesian networks are less computationally demanding and have less impact on energy consumption. The results presented in Section 5 show that, although the success rate of the Long Short-Term Memory [20] recurrent neural network to classify our barometric pressure data was very high (only 0.9% of errors, on average), the J48 decision tree algorithm also had a very good performance, providing an average recognition rate of about 95%. For all these reasons, J48 algorithm is the best choice for detecting VDAs on smartphones using barometric pressure data. We also directly measured battery consumption when sampling barometric pressure at a constant rate and found that it is negligible. To demonstrate the advantages of using pressure sensors for activity recognition over sensors traditionally used (i.e., accelerometers and GPS), in Section 6 we analyse and compare accuracy, energy efficiency, indoor effectiveness and phone position independence. Finally, in Section 7 – as a use case scenario – we describe an App for Android where both barometer-based approaches to activity recognition and height estimation have been implemented. This App detects user activity using the J48 decision tree algorithm and shows the altitude graph, the current vertical speed and some statistics about the activities performed by the user.

2. Related work

Many studies have focused on the identification of human VDAs, such as standing, walking, climbing stairs and riding up/down an elevator, from sensors data.

Several pieces of work have been performed with the analysis of accelerometer data, as further discussed in Section 6.1. In general, the accuracy of methods based on accelerometers depends on the position of the sensors (or the phone that embeds sensors) and accelerometers are energy-demanding. Kwapisz et al. [21] collect data from a phone's accelerometer for 29 individuals. Data is analysed and two patterns are identified (periodic and non-periodic). Then, they use three classification techniques (decision trees, logistic regression and multilayer neural networks) to predict the user activities. Krishnan and Panchanathan in [22] evaluate the performance of different discriminative classifiers (i.e., Boosted Decision Stumps, Support Vector Machines and Regularized Logistic Regression) to tackle continuous human activity recognition based on accelerometer data. They propose to capture the rate at which the acceleration changes for activities that have a significant amount of motion (like walking, running, etc.), by computing statistical features like mean, variance and correlation on the first order derivative of the acceleration data. The human-activity recognition system proposed in [14] employs a smartphone with a built-in triaxial accelerometer. It uses a combination of statistical signal features, artificial-neural nets and autoregressive modelling to classify activities. The most cited paper about activity detection using accelerometers is [23], where authors (Bao et al.) use wearable accelerometers to classify a variety of every-day activities (including standing, climbing stairs and riding elevator). In [24] barometric pressure data is used in combination with tri-axial acceleration data and tri-axial gyroscope data to train classifiers and recognize child activities. In [25] pressure sensors are used to improve activity recognition based on acceleration data: in this case, authors limit to plot measures of both barometric pressure and acceleration, and to observe that the change in altitude connected to a pressure change can help to provide a more sophisticated algorithm for activity recognition, but they do not propose any algorithm for activity detection. In [26] a dedicated multi-sensor board containing seven different sensors (microphone, visible light phototransistor, 3-axis accelerometer, 2-axis compass, barometer, ambient light, and humidity) is used to collect measurements from twelve individuals, to infer a subject's activity and classify it as sitting, standing, walking, walking up stairs, walking down stairs, riding elevator down, riding elevator up, and brushing teeth. They employ an ensemble of classifiers to select the most useful features and then use those features to recognize the set of human movements. A second layer of Hidden Markov Models (HMMs) combines the outputs of the classifiers to estimate the most likely activity. Results show that three sensors yield the most discriminative information for recognizing activities: the audio, barometric pressure and accelerometer sensors. This information is complementary: audio captures sounds produced during the various activities, accelerometer data is sensitive to the movement of the body, and barometric pressure helps detecting activities connected to height variations, such as riding an elevator or moving up and down stairs. In [27], four sensors (accelerometer, barometer, gyroscope and magnetometer) are employed to accurately recognize a user's mode of motion when a height change is detected. The algorithm developed has shown a good success rate (from 80 to 96%) in discriminating among walking up or down stairs, riding an elevator, and standing or walking an escalator. In very few pieces of work, GPS location data has been used to learn and recognize the activities in which a person is engaged over a period. For example, in [28] the authors extract a person's activities – such as walking, driving a car, or riding a bus – from traces of GPS data,