HAL
open science

On the Challenges and Potential of Using Barometric Sensors to Track Human Activity

Ajaykumar Manivannan, Wei Chien Benny Chin, Alain Barrat, Roland Bouffanais

To cite this version:

Ajaykumar Manivannan, Wei Chien Benny Chin, Alain Barrat, Roland Bouffanais. On the Challenges and Potential of Using Barometric Sensors to Track Human Activity. Sensors, 2020, 20 (23), pp.6786. 10.3390/s20236786 . hal-03031690

HAL Id: hal-03031690

https://hal.science/hal-03031690v1

Submitted on 30 Nov 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

MDPI

Review

On the use of barometric sensors to track human activity

Ajaykumar Manivannan [1], Wei Chien Benny Chin [1], Alain Barrat [2,†,‡] and Roland Bouffanais [1,‡*]

[1] Singapore University of Technology and Design, 8 Somapah Road, 487372, Singapore. ; manivannan_ajaykumar@mymail.sutd.edu.sg (M.A.); benny_chin@sutd.edu.sg (B.C.); bouffanais@sutd.edu.sg (R.B.)
[2] Aix Marseille Univ, Université de Toulon, CNRS, CPT, Marseille, France; alain.barrat@cpt.univ-mrs.fr (A.B.)
* Correspondence: bouffanais@sutd.edu.sg; Tel.: +65 6303 6667
† Tokyo Tech World Research Hub Initiative (WRHI), Tokyo Institute of Technology, Tokyo, Japan.
‡ These authors contributed equally to this work.

Version November 30, 2020 submitted to Sensors

Abstract: Barometers are among the oldest engineered sensors. Historically, they have been primarily used either as environmental sensors to measure the atmospheric pressure for weather forecast, or as altimeters for aircrafts. With the advent of MEMS-based barometers and their systematic embedding in smartphones and wearable devices, a vast breadth of new applications for the use of barometers has emerged. For instance, it is now possible to use barometers, in conjunction with other sensors, to track and identify a wide range of human activity classes. However, the effectiveness of barometers in the growing field of human activity recognition critically hinges on our understanding of the numerous factors affecting the atmospheric pressure, as well as on the properties of the sensor itself—sensitivity, accuracy, variability, etc. This review article thoroughly details all these factors and presents a comprehensive report of the numerous studies dealing with one or more of these factors, in the particular framework of human activity tracking and recognition.

Keywords: Barometer; Barometric pressure; Human activity recognition (HAR); Vertical displacement activity (VDA)

1. Introduction

Barometers have been around for a very long time. While the air was thought to be weightless till the early 1640s, this changed when the Italian physicist and mathematician Evangelista Torricelli showed that a column of air exerts a significant force that can be measured by the amount of liquid displaced by the pressing air. This led to the discovery that "air has weight", and the invention of a measurement device that quantifies the atmospheric pressure [1]. In the latter part of 1640s, Blaise Pascal perfected the experiment and showed the finiteness of air pressure, leading to the hypothesis that the height of the atmosphere itself is finite, and to the proposition that altitude can be measured as proportional to the atmospheric pressure [2]. The SI derived unit, the Pascal (Pa), is named after Pascal's contributions to hydrodynamics, and is now officially used to measure the force applied by an atmospheric column of air above a unit surface area.

For the first two centuries after the invention of the barometer, this device was constructed using glass tubes filled with liquids such as water or mercury [3]. In 1844, a new design appeared with the development of the aneroid barometer, that is purely mechanical, does not contain liquids, and shows the measurement value on a face dial [4]. These devices took a quantum leap with the advent of micro-fabrication in the 1960s that allowed the miniaturization of the barometer and accelerometer to a

size smaller than 0.1 mm, what is now commonly known as Micro Electro Mechanical Systems (MEMS). With the successive advancements in integrated-circuits and digitization of the sensor readings, the manufacturing and the computational cost of these miniaturized devices were significantly driven down, thus paving the way for their widespread adoption in consumer products, especially in mobile phones. Currently MEMS-based barometers are by far the most commonly found type of barometers in wearable devices and smartphones. In 2015, one of the pioneers in MEMS manufacturing, Bosch (Robert Bosch GmbH) claimed to manufacture 1 billion MEMS sensors per year for automotive and non-automotive applications in one production facility in Germany [5]. This company also claims to have their MEMS devices (including barometers) embedded in every second smartphone in the world [5]. Although this claim cannot be independently verified, it still points to the massive scale of production for this type of sensor, and underscores the ubiquitous availability of MEMS barometers.

Historically, barometers were used for weather forecast and thus chiefly as environmental sensors. As a measurement device of ambient pressure, barometers have been recently used to measure evapotranspiration (transfer of water from land to atmosphere) in a given environment, improving motor vehicle engine efficiency by modifying air-fuel mixture, and to count steps based on the slight disturbances in air pressure during body movements [6]. Thanks to the relation between pressure and altitude, barometers are also widely used as altimeters to measure altitude, in particular in airplanes and Unmanned Aerial Vehicles (UAVs). Recent applications include their use in warehouses for precise automated placement, retrieval, and monitoring of objects on shelves, and indoor/outdoor navigation of humans and vehicles. It is worth highlighting that there is still significant opportunities for the use of barometers in a vast range of additional applications. Clearly, the full potential of barometers has not yet been taken advantage of, in particular in the Internet of Things (IoT) realm and with future consumer devices, particularly in the fast-growing area of wearable devices.

In particular, the ubiquity of MEMS barometers in smartphones and other wearable devices makes them natural candidates as data sources for the study of human activities and to the field of Human Activity (and mobility) Recognition (HAR) [7]. Broadly speaking, HAR consists in using data from various types of sensors carried by individuals to automatically understand what type of activity they are carrying out. It consists therefore in choosing sensors that will be influenced by the activity, annotating a certain amount of data (that will serve as "training data") thanks to ground truth knowledge (i.e., the knowledge of the precise conditions in which the data was collected), and devising a classification task using typical machine learning frameworks to classify the rest of the data. The human activities considered can be broadly classified under two main classes: (1) Ambulation, and (2) Transportation [7]. Ambulation refers to all movements and idle states of our human body (walking, idle, running, sitting, etc.), while transportation refers to our movement through vehicles (cars, buses, bicycles, etc.) [7]. In HAR research, such activities are considered under two conditions: (1) Natural ones, and (2) Laboratory. These conditions lie at the two extremes of a spectrum: "natural" refers to individuals behaving normally, within their usual environment, without any defined procedure and without being influenced by their being monitored, while laboratory conditions refer to a set-up that is especially designed for a human subject, who is given explicit instructions to perform a given activity. In reality, most experiments with human subjects happen somewhere in between these two extreme conditions.

Inertial Measurement Units (IMU)—comprising accelerometer and gyroscope, along with magnetometer—are the most commonly used sensors to track human activity. Although the first accelerometer was invented by the English physicist George Atwood in 1783, this sensor has not been used in any commercial applications till the 1920s, but this changed with the advent of motor vehicles, including airplanes [8]. Smartphones have been equipped from the start with accelerometers, whose signals are widely used to recognize most activity classes [9].

Until the 1990s, it seems that there is almost no reference in the literature to the use of barometers in tracking human activities. That changed with the silicon and digital revolution, which contributed to the effective use of barometers to track a range of human activities in the late 1990s. Initially, consumer

devices such as mobile phones were equipped with barometers to improve GPS-based localization by reporting altitude or altitude changes [9]. Today, barometers along with a suite of sensors like IMU and magnetometer are used—individually or through sensor fusion—to track a wide range of human activities. Such use of barometer to track human activities is a fairly recent phenomenon. In the last two decades, the barometers were found to improve some activity class recognition that involves change in height, such as fall or vertical mobility. In some applications such as recognizing Vertical Displacement Activity (VDA), the accelerometer has been replaced by or at least given less importance than barometers, which are more energy efficient, require less signal processing and yield less noisy signals than IMU signals. Most smartphones have barometers allowing to predict changes in altitude with an accuracy of the order of 1 meter. However, an effective tracking of human activities is best obtained with the combined use of these important sensors, each providing unique information on the subject's state.

It is however important to note that our ability to properly leverage the potential of barometers for HAR purposes critically hinges on our understanding of the physical properties of the atmospheric pressure. Indeed, the measure of the ambient pressure by a barometer is influenced by the static and dynamic properties of its environment [**?**]. Its effective use as a signal thus requires dedicated data post-processing techniques and classifiers, in general to account for external factors: for instance, if one is tracking altitude changes and vertical displacement activity, the variations in the local atmospheric pressure have to be accounted for. Measures are moreover affected by the sensor itself, whose accuracy and manufacturing imperfections can introduce noise and variability between devices. Hence, it is fair to say that the numerous factors affecting barometric pressure (see Sec. 4), if not properly understood and accounted for, can hinder the effective use of barometers to detect and identify particular classes of human activity.

The current review is non-exhaustive but intentionally limited to the use of barometric sensors for the most common classes of human activity. This choice is justified by the wide range of applications offered and the fact that barometers now pervade many mobile devices (wearables and smartphones, cars, etc). The applications explored are also primarily limited to the recent developments in using MEMS-based barometers for consumer goods/electronics. It is worth stressing that this review does not address the vast breadth of Machine Learning (ML) or other advanced classifiers used to interpret the sensed data, and identify a given activity with a given accuracy. However, the details provided in this review are most useful for the further development and design of effective ML/classifier strategies.

This review is organized as follows: Sec. 2 introduces the general sensor data collection process to track human activity. Section 3 looks specifically into the use of barometers in human activity and mobility recognition. Section 4 describes the factors that affect barometric pressure and quantifies the order of magnitude of each effect based on a range of studies reported in the literature. This section is enriched by data especially collected for illustration purposes. Lastly, Sec. 5 explores the potential directions of future research in HAR using barometric sensors.

2. General sensor data collection process to track human activities

Barometers are part of the suite of sensors used to track, recognize, analyze, and ultimately understand human activities. As such, the characteristics of the data collection process is similar to the one of other types of sensors. They include the characteristics of sensors, their placement and orientation, the sampling frequency, the environmental conditions. The type of application (activity class, diversity of sample population) and the method to record the ground truth and annotate a part of the data have also to be carefully designed. Data collection and annotation are indeed critical to the effectiveness of subsequent stages of classification—e.g., data pre-processing, feature engineering and identification—in the overall workflow of sensed data associated with human activity recognition. Similarly, an informed decision on the data collection procedure depends on the specific problem under study and on the particular class of human activity being investigated. Depending on the sensor characteristics and the class to be recognized, data collection methods must be tailored to shed light

on the phenomena under investigation for better accuracy and performance. The success of such data-processing activity not only depends on acquiring the data, but also in being able to effectively process it and extract meaningful features and patterns.

2.1. Sensors and sensor suites

Smartphones and watches are by far the most common and straightforward way to collect data in a natural setting. Nonetheless, some research groups studying particular behaviors and phenomena required a custom-built wearable sensor design for both laboratory testing as well as for operations in real-life conditions. For instance, 3-axis accelerometers are the most widely used sensors [10,11], followed by 3-axis gyroscopes and magnetometers. Since these inertial sensors are now commonly found in today's smartphones and other MEMS devices, many recent studies use a combination of these sensors to improve classification accuracy [12,13], although a 3-axis accelerometer alone can extract good quality data resulting in excellent classification results [14]. Wearable devices may also contain environmental sensors that measure for instance temperature, light, atmospheric pressure and sound to assist in context detection, and/or physiological sensors such as heart rate for medical research [7] and personal fitness purposes. In transport mode recognition, GPS is the most widely used sensor [15], followed by telecommunication data [16,17], WiFi access points [18,19], and travel surveys [20]. In general, location-based sensors operate based on a combination of inertial sensors to build robust recognition systems that can distinguish between different travel modes, including walking and being idle [21]. Fusion of environmental sensor data with inertial and location-based sensed data provides sufficient information to detect what is commonly known as 'Activities of Daily Living' (ADL). In this context, barometric pressure sensors have traditionally been considered as environmental sensors used to measure ambient pressure. However, they are also capable of sensing movement/activity in ways similar to inertial sensors, especially when considering vertical movements.

2.2. Placement and orientation of the sensor

Placement and orientation of the sensor might influence the characteristics of the captured signal thereby affecting the recognition accuracy: indeed, the training data might then fail to account for all the possible variations, resulting often in a sparse feature space. Numerous studies have focused on ways to alleviate this particular effect, and provided solutions that range from collecting diverse data to independent features not affected by such parameters [22–24]. Chen et al. [25] proposed the use of coordinates transformation along with principal component analysis (PCA) to reduce this issue associated with orientation changes. Several groups have also studied the question of optimal sensor placement [26,27]. Interestingly, while this issue affects many sensors, this is not the case for barometric pressure sensors whose readings are widely independent of their on-body position and orientation [28], even if they are dependent on a range of environmental conditions.

2.3. Sampling frequency

The temporal resolution of the data is directly related to the sampling frequency of the sensor used. For the vast majority of sensors used to carry out human activity recognition, the sampling frequency typically ranges from 10 Hz to 100 Hz, with the rate going as high as 512 Hz. It is commonly reported that the characteristic frequencies of most human activities are below 10 Hz, and therefore the optimal sampling rate— based on the Shannon–Nyquist theorem—is 20 Hz [29]. Khan et al. [30] reviewed 5 public datasets and showed that the sampling rate considered could be reduced between 48% and 86%, with a minimal sampling rate of approximately 12 Hz [30]. Yan et al. [31] also studied the effect of sampling rate on energy consumption and they concluded that a higher sampling rate increases energy load without providing additional meaningful information, in agreement with the results reported in [30]. From the energy perspective, Yan et al. [31] concluded that a shorter dataset with a higher sampling rate is preferable to a longer dataset at a lower sampling rate. It is worth adding that the optimal sampling rate also depends on the type of human activity to be recognized [30]

and on the type of sensor used. For instance, when studying human mobility, sampling GPS data or other location signals at rates comparable to those of accelerometers is unnecessary. Hence, the GPS signals are typically sampled at around 1 Hz [32,33]. For pressure signals, barometers have been sampled at rates as low as 1 Hz [34].

2.4. Activity classes

Lara & Labrador [7] thoroughly reviewed a comprehensive list of human activities recognized and categorized in the literature, including ambulation, transportation, gestures, exercises and daily living activities. The activity classes may of course occur concomitantly and may therefore be composite [35], interleaved, concurrent or overlapping [36]. For data with low sampling frequency, i.e. lower than 1 Hz, more than one activity could be performed during the same time interval. In particular, the class of vertical displacement activities (VDA) has generally been recognized in the literature as part of the larger class of ambulation activities. Similar to accelerometers, barometers are very well suited for the recognition of VDA. In addition, barometers can accurately determine altitude changes for VDA occurring at a sampling rate lower than 1 Hz.

2.5. Nature of data

Several groups have collected their own datasets to fit the specific needs and requirements of their studies [37,38]. Many benchmark datasets are also publicly available, and are commonly used to validate new methods [39–42]. The recent review article [43] reported details of several key benchmark public datasets and provided a rich analysis on the content and application-context studies. The datasets collected and made available publicly either were collected in laboratory conditions [44], or are real-world ones—where participants had instructions to perform specific activities given implicitly [45], explicitly [24], or instead were allowed to move freely while being unobtrusively observed [13]. These datasets have been claimed to be semi-naturalistic or realistic even when the subjects were given scripted instructions [46,47]. Lara & Labrador [48] reported on subjects performing interleaving activities as they naturally occur, in sequence rather than segmented to reach realistic conditions. Truly realistic data correspond to data collected while people go about their Activities of Daily Living (ADL) [14]. As highlighted in [49], the use of purely realistic data would however require a long data collection period. Hence, segmented data obtained by a set of experiments corresponding to various activity classes are typically collected for training. Some studies such as [50] and [51] have managed to deal with this issue by considering segmented data for training and activities of daily living or sequence data for validation.

2.6. Class imbalance

The problem of class imbalance in datasets—the fact that some activities are more prevalent than others and are therefore over-represented— is a recurrent condition found in both public and private datasets and known to affect recognition accuracy [47,52,53]. For instance, data corresponding to physically tiring activities, or difficult to obtain for other reasons, naturally forms an under-represented portion of the data, thereby leading to inherent data imbalance [38]. This issue can be offset by oversampling the minority class or under-sampling the majority class. Chen & Shen [38] used the so-called Synthetic Minority Over-sampling Technique (SMOTE) for oversampling the minority class while Trung [54] used a modified version of it. Guan et al. [52] also proposed to use an ensemble of deep learning models to offset such data imbalance. Other studies have tackled the problem by simply using F1-score to report classification accuracy that takes into factor the different sizes of each class [52,55]. This issue can occur in applications using barometers, as the number of altitude changes in human mobility for any given continuous experiment is usually very limited, and these changes have moreover typically a rather high inter-event time in ADL.

2.7. Diversity in physical characteristics

Data collection methods can contribute to the generalization in recognition models by allowing diverse characteristics or parameters to be incorporated into the training dataset. These characteristics should be representative of the final dataset to which the model is applied. One of the important parameters is the user herself, whose diverse physical characteristics can be challenging to integrate or model [37]. Studies generally report the user's age, height, weight, body mass index (BMI) and physical ailments, etc. for context and applicability of the study [55–58]. In the case of barometers, the height of the user/carrier has only a limited effect on the use of a barometer, and the resolution of most wearable sensors are within the range of placement difference. It is thus safe to assume that the barometer sensor works independently of the physical characteristics of the carrier.

2.8. Annotation techniques

Stikic et al. [59] note that the accuracy of annotation is subject to a trade-off between length of the data collection and the time and effort required for labelling the dataset. Indeed, if direct observation is required for accuracy, this results in a prohibitively expensive requirement. De la hoz Franco et al. [43] carried out a meta review of 374 papers on Human Activity Recognition (HAR) and found that 60% of the used data were annotated. However, most studies record ground truth by resorting to experiments in a laboratory setup with the help of researchers and supporting infrastructure [27,57,58]. Some studies have also relied on subject self-reporting [37,60,61], which are known to be error-prone due to the obvious difficulty in marking precise times while carrying out the activities of daily living. Chung et al. [13] recorded ground truth by unobtrusively following the subjects one at a time. Video capturing [34,47,55,62], audio recording [63] and GPS localization have been highlighted as methods of direct observation without requiring to monitor the subjects under constrained controlled conditions. Recording ground-truth data for long term studies of ADL has been repeatedly acknowledged to be impractical and/or prohibitively manpower intensive [49,64]. For instance, Willetts et al. [14] used automatic cameras to record ground truth every 20 seconds for 143 participants over 24 hours. This shows the interest of automated methods such as the active learning methods developed by Bota et al. [50] that require the manual annotation of a small subset of the data, while the rest is automatically labeled.

A practical, privacy-sensitive and unobtrusive annotation method for studies using barometers to track humans over long durations is manual labeling of the data. Unlike the signal sensed by accelerometers or other inertial sensors, barometric pressure can indeed be less complex to interpret. However, this process comes with several challenges, one of which being the lack of complete understanding of all the factors that influence barometric pressure. This important issue is addressed in detail in Section 4.

3. On the use of barometer in human activity and mobility recognition

For the sake of studying human activity and mobility recognition, the barometer has been primarily used to measure changes in altitude (or elevation). The scale of the altitude changes varies from a fall to vertical displacements like moving uphill, climbing a deck of stairs, riding an elevator, etc. In recent applications, the patterns of the time series of barometric signals are shown to be a good indicator of the underlying activities such as walking, idle and transportation. The rate of pressure change can help to identify the mode of vertical transport and determine the vertical velocity of air vehicles. Barometers are widely embedded in wearable devices and used for vertical transport detection [28,65–70], indoor positioning and navigation [68,71–73], building monitoring [74], health monitoring [75,76], vehicle tracking [77,78], transport mode detection [79], and GPS localization improvement [68].

One of the earliest works on using barometer to classify vertical movement is due to Sagawa et al. [80] and dates back to 1998. In [80], Sagawa et al. collected 83 minutes of data using both

accelerometer and barometer at a 100 Hz sampling frequency from 6 males between 20 and 40 years of age. Their classification model was trained offline using cut-off values selected heuristically. Since then, recognition and identification procedures have greatly improved thanks to a number of factors including: new sensor types, larger range of sampling rates, user and device characteristics, modes of carriage, power consumption, real-time demand, classification models, and finally ground truth availability.

3.1. Barometric pressure sensor

MEMS Barometers are miniature sensors (< 0.1 mm) manufactured by prominent companies such as Bosch [77,81,82], ST Microelectronics [77,81,83], and Measurement Specialities [84]. As mentioned previously, they are commonly found in wearable devices and smartphones. They have high precision but relatively lower absolute accuracy than table-top barometers. Specifically, the accuracy in measuring absolute pressure is low in these sensors but their relative pressure accuracy is shown to be as low as ± 1.2 Pa [84,85], with average mobile devices having resolution of ± 12 Pa [28]. It is worth adding that the measured absolute pressure varies from one device to another due to manufacturing differences and other technical factors [81].

3.2. Processing barometric sensor data

Barometers are constrained by their resolution and sampling frequency, which limit precision and accuracy, and the use of their data is further constrained by the presence of noise. Some studies have used filtering and signal modeling to overcome the latter problem. For instance, moving average filters over a given time window is widely used for that purpose [71,84,86], followed by other Finite Impulse Response (FIR) filters [87] and Infinite Impulse Response (IIR) filters [76,87–89] such as double exponential smoothing [28,69]. Signal modeling like sinusoidal fitting model [90] and sigmoidal nonlinear fitting are commonly used to increase the contrast of elevation changes [91].

The time series data of barometric pressure is generally converted to statistical [70,92], spectral [70,92], temporal [70,92] or wavelet-based features [75,93], before being fed into a classifier. These features are designed to enhance the detection of the specific activity of interest. Most used features are based on the rate of change of pressure [69,70,79,84,94] (also known as vertical velocity or simply the slope) and the standard deviation of differential pressure (dp) [74,79], that differentiates altitude changes from other environmental factors that influence ambient pressure.

3.3. Classifiers for sensed barometric pressure

The choice of the classifier depends on the application at hand. It also depends on the range of pressure variations and durations under consideration. Some studies have only considered indoor pressure profiles of individuals [28,68], while few have considered the full Activities of Daily Living (ADL) that include both indoor and outdoor events like transportation [77,79]. A person carrying a barometer is indeed affected by factors present outside their specific environment, which seriously limits the scope of many studies of HAR using barometer data.

Barometric pressure is more straightforward than inertial sensors in conveying sensed information due to its fairly direct reading, which greatly simplifies the use of classifiers. The most widely used classifiers are decision trees [28,65,68,82,83,87], Support Vector Machines (SVM) [75,77,95,96] and threshold based models [76,91,97,98]. Clustering models such as hierarchical clustering [73,99] and k-Means clustering [71], Bayesian-based classifiers [72,100,101], LSTM models [28,102] and fuzzy inference models [90] have also been used. Hidden Markov Models take advantage of logical activity sequences that can be associated with some activity sequences (such as riding an elevator before and after walking) [103], while fuzzy inference models take advantage of context and behavioral constraints [90].

Liu et al. [69] compared classifiers such as Random Forest, J48 decision trees, Artificial Neural Networks (ANN), SVM and Naïve Bayes to classify horizontal displacement activity from vertical

displacement activity; the Random Forest classifier was found to have the highest accuracy. Vanini et al. [28] compared the performance of Bayesian networks, Decision trees and Recurrent Neural Network (RNN) models to recognize VDA. It has been found that RNN have a 99% accuracy while Decision trees provide the optimal trade-off in terms of computational cost, energy efficiency and accuracy.

Some applications do not require any classifiers. For instance, state estimation like altitude and vertical velocity can be determined using a Kálmán filter or one of its many variants [86,96,104–106]. As another example, Bollmeyer et al. [84] solely used the differential pressure to estimate altitude. Ho et al. [78] used the so-called Dynamic Time Warping (DTW) technique to establish the correlations between the pressure time series data and known geographical elevations to track vehicles. Similarly, Hyuga et al. [107] found ways to use the variance of differential pressure to account for the variations in barometric pressure associated with air velocity and the built environment; they used similarity measures between pressure and known altitude to locate a train/user in a rail network.

3.4. Applications

Barometer-only studies: Very few studies dedicated to tracking human activity and/or mobility are solely relying on the use of a barometer, despite the fact that their potential for applications is promising. For instance, barometers have been used to measure altitude as a stand-alone measuring instrument for a very long time. Taking this concept one step further, Bolanakis [81] used a dual-device system to estimate the altitude of an airplane above a landing area and find the orientation angle of wings.

The surface of the land on which we move and travel, including transportation routes, is uneven. This topographical feature can be estimated using barometric pressure, and the subtle changes in elevation along the travel routes can be exploited for localization of vehicles. As stated before, this is however challenging due to two major factors that affect barometric pressure—built environment like tunnels, bridges, etc., and the air velocity during motion. However, Hyuga et al. [107] used the pauses of trains in stations between successive train rides to locate a user/train in a subway route by computing the successive altitude changes and comparing them with known relative elevations of train stations.

Similarly to accelerometer data, the signal pattern encoded in a barometer output carries sufficient information to recognize a range of human activities. Ghimire et al. [87] observed the change in air pressure when a person walks with hands swinging and used this gait pattern to count steps. The pressure fluctuations due to vehicle motion was used by Sankaran et al. [79] to differentiate between the distinct patterns produced by vehicles as opposed to walking and standing idle.

In climate controlled buildings, changes in barometric pressure can be detected during indoor-to-outdoor transition. Wu et al. [74] moreover showed the possibility to detect the opening or closing of a building's entrance doors, even with a barometer located far from the doors, and even analyzed the patterns to determine the type of door (automatic or manual). They highlighted implications to building monitoring and security.

Applications that use only barometer data are more common in the studies concerned with floor localization and recognition of VDA. In the absence of location sensors, the challenge with floor localization is to have a reference pressure and associate it with the data measured by the considered wearable devices at the moment they enter a given building. To obtain such a reference pressure, Li [108] recommends receiving it from a location that is similar to the environment in which it is deployed; this setup is important as the reference pressure obtained from reference stations can potentially experience different environmental effects. Xia et al. [66] showed that the barometric pressure pattern can change from floor to floor in idle settings, and hence, installed a calibrated barometer in each floor to collect multiple reference pressures. Ye et al. [99] applied an infrastructure-independent approach by constructing an encounter network—determined by comparing simultaneous pressure changes—and use a root node to calibrate all the mobile sensors.

This method is of course prone to errors and the lack of calibration has been shown to result in an accuracy of only 70%.

The challenge for recognizing VDA using only barometer data is that the sensor data should ideally be free from all factors other than altitude that affect barometric pressure. This can be guaranteed if the sensor data is collected from a controlled environment where no other factors that can be mistaken for VDA occur. As shown by Bollemeyer et al. [84], Ghimire et al. [87], and Muralidharan et al. [68], this can be achieved by limiting the studies to indoors where only weather, sensor accuracy and built environment effects are impacting the barometric readings. Liu et al. [104] collected experimental data from outdoors like mountain climbing while avoiding activities that cause adverse pressure gradients like transportation. Vanini et al. [28] have demonstrated their VDA recognition capability while considering ambulation and transportation, with however a limited set of activities, including in particular only cable-cars as outdoors transportation mode.

In summary, in a specific environment and considering selected modes of activity, recognition performance of VDA using barometer can be very high. More generally, in any given environment, barometers are shown to perform far better or similarly to other sensors when detecting VDA, and represent the only viable way to extract the magnitude of vertical displacement. Vanini et al. [28] report that with barometer data, one achieves similar performance in classifying VDA compared to accelerometer and GPS, but a superior one in energy efficiency and independence in terms of sensor location and orientation. Muralidharan et al. [68] similarly showed that barometer-only classification is significantly more accurate (99%) in recognizing modes of VDA compared to accelerometer-based classification (85%). However, the accuracy for accelerometer-based classification drops below 30% when the mobile phone is used for taking calls or playing games.

Multi-sensor studies: As just mentioned, few studies have employed barometer as the sole sensor in their application. It is usually integrated with other sensors like inertial sensors [69,82], environmental sensors (light, temperature, sound, etc.) [109,110], location-based sensors (GPS) [71,96], and communication infrastructure (WiFi, Bluetooth, RFID, etc.) [72,73,100,110]. Several studies are dedicated to improving the sensor fusion of inertial sensors with barometer, which constitutes a critical step in the optimization of activity recognition [86,110,111].

In most classical HAR analyses, the classification accuracy in detecting VDA based on sensory data without pressure is usually low [89]; this is not seen as a critical issue since VDA is not the focus or priority. Increasingly, barometer has been recognized as an important sensor in HAR, where accurate recognition of VDA is critical to many applications [106]. Hence, a majority of applications that aim to measure altitude or track altitude changes employ a barometer as part of their sensory suite. For instance, in health monitoring applications, the inclusion of barometer has been shown to improve VDA recognition [44,75,95], fall detection [76,83,93], estimation of energy expenditure and physical activity [44,91,97,112].

Accelerometers are still the predominantly used sensors in HAR, and have been widely used as stand-alone sensors in recognizing many activities of daily living. They complement barometer-based recognition algorithm in detecting ambulatory movements such as walking, and their use helps also distinguish stairs climbing from other modes of vertical transportation like elevator and escalator [69, 101]—and even elevator from escalator [67]. Sankaran et al. [79], however, point to the high cost associated with the use of accelerometers: demands in data acquisition (position and orientation dependent), high sampling rate, complex processing and classification training.

For indoor localization and navigation applications, obtaining reference pressure to calibrate all mobile sensors is critical for the system to work. This is more easily obtained in multi-sensor applications. Pipelidis et al. [71] used light sensors to detect the transition between indoor and outdoor so as to derive a reference pressure at ground level, which subsequently serves the detection of floor levels. Communication infrastructures like WiFi, Bluetooth and RFID are also used to provide additional location information to help assist indoor localization or transmit location specific data such as reference pressures in a floor to assist barometers for calibration purposes. Tachikawa et al. [110]

even combined WiFi signal with microphone and other inertial sensory data to detect the type of indoor location—restroom, desk, elevator, etc.

Barometers are known to speed up the GPS localization through their altitude estimation [68]. Conversely, the altitude information can be accessed from GPS localization [104]. Furthermore, GPS or any location information can help distinguish the transportation modes from ambulation, where the changes in barometric pressure can easily be misunderstood for altitude changes. Even though the elevation changes are present in our transportation paths, the altitude estimation from barometric pressure due to air velocity during motion can be predominant. Some studies have used the barometric pressure instead of GPS to track a vehicle [44,77], but this can be very misleading as the significant changes in pressure due to vehicle motion and the built environment like tunnels and bridges have not been fully taken into account or even properly understood.

To summarize and categorize the vast breadth of applications of barometers for HAR, we have gathered all this information into Table 1.

Table 1. Categorized literature related to the application or use of barometers for human activity recognition

Reference	Sensors	Use of barometer	Factors considered influencing barometric pressure	Contributions and applications	Activity class	Location	Time period
[111]	Barometer, Accelerometer and Gyroscope	Estimate altitude and correct accelerometer errors	Altitude	Improved IMU-Barometer Sensor fusion	–	Indoor	Short term
[82]	Barometer, Accelerometer and Gyroscope	Estimate altitude changes	Altitude	Identify ambulation activities including VDA	Ambulation	Indoor	Short term
[71]	Barometer, Light and GPS	Estimate altitude and floor level	Altitude	Vertical indoor mapping	Ambulation	Indoor and outdoor	Short term
[101]	Barometer and Accelerometer	Calculate vertical displacement and estimate floor level	Altitude, climate and weather, and built environment	Floor localization	Ambulation	Indoor	Short term
[86]	Barometer, Accelerometer and Gyroscope	Estimate altitude changes	Altitude and Climate & Weather	Improved sensor fusion to track vertical motions	Ambulation	Indoor	Short term
[72]	WiFi and Barometer	Estimate altitude and altitude changes	Altitude, climate & weather and sensor accuracy	Improved barometer measurement error model and sensor fusion for floor localization	Ambulation	Indoor	Short and long term
[93]	Barometer and Accelerometer	Estimate altitude changes	Altitude	Improved accuracy by including barometer for fall detection	Ambulation	Indoor	Short term
[89]	Barometer, Accelerometer and Gyroscope	Estimate altitude changes	Altitude	Improved accuracy in recognizing ambulation activities including VDA	Ambulation	Indoor	Short term
[112]	Barometer and Accelerometer	Estimate altitude changes	Altitude, climate & weather and sensor accuracy	Detection of VDA improved the estimation of energy consumption and physical activity	Ambulation	Indoor and outdoor	Short and long term
[73]	WiFi and Barometer	Estimate altitude	Altitude and sensor accuracy	Improved floor localization from crowd sourcing using few devices equipped with barometer	–	Indoor	Short term
[85]	Barometer	Estimate altitude	Altitude, climate & weather and sensor accuracy	Barometer measurement error modeling and correction to track air vehicle	–	Outdoor	Short term
[68]	Barometer	Estimate altitude changes and mode of vertical transportation	Altitude, climate & weather, built environment, and sensor accuracy	Identify VDA and mode of vertical transport	Ambulation	Indoor	Short and long term

[76]	Barometer and Accelerometer	Estimate altitude changes	Altitude	Improved fall detection using barometer	Ambulation and transportation	Indoor	Short term
[104]	Barometer	Estimate altitude	Altitude, climate & weather, and sensor accuracy	Estimation of altitude for indoor and outdoor	Ambulation	Indoor and outdoor	Short term
[92]	Barometer and Accelerometer	Estimate altitude changes	Altitude	Reduced position and orientation dependency using barometer	Ambulation	–	Short term
[95]	Barometer and Accelerometer	Estimate altitude and altitude changes	Altitude	Child activity recognition including VDA to prevent injuries	Ambulation	Indoor	Short term
[105]	Barometer and Accelerometer	Estimate altitude changes	Altitude, climate & weather and sensor accuracy	Earliest known activity classification including VDA using barometer	Ambulation	Indoor	Short term
[97]	Barometer and Accelerometer	Estimate altitude changes	Altitude and sensor accuracy	Detection of VDA improved the estimation of physical activity and energy expenditure	Ambulation including cycling	Indoor and outdoor	Short term
[75]	Barometer, Accelerometer, Magnetometer and Gyroscope		Altitude, built environment and sensor accuracy	Activity recognition including VDA for health monitoring of stroke patients	Ambulation	Indoor and outdoor	Short term
[65]	Barometer, Accelerometer and Magnetometer	Estimate altitude changes	Altitude, built environment and sensor accuracy	Identify mode of vertical transportation for indoor navigation	Ambulation	Indoor	Short term
[69]	Barometer, Accelerometer, Magnetometer and Gyroscope	Estimate altitude changes	Altitude, climate & weather, built environment and sensor accuracy	Improved recognition of VDA using barometer	Ambulation	Indoor	Short term
[67]	Barometer, Accelerometer, and Gyroscope	Estimate altitude changes	Altitude	Improved identification of VDA for indoor localization	Ambulation	Indoor	Short term
[44]	Barometer and Accelerometer	Estimate altitude changes	Altitude	Using barometer improved overall activity recognition including VDA and better estimate of energy expenditure	Ambulation	Indoor	Short term
[107]	Barometer	Estimate altitude and altitude changes	Altitude, air velocity during motion, and built environment	Estimate the location of traveler in a subway using only barometer	Transportation	Outdoor	Short term
[81]	Barometer	Estimate altitude and altitude changes	Altitude, climate & weather, and sensor accuracy	Evaluate sensors to estimate the altitude of airplane above ground and the orientation angle of wings using dual device systems	–	Indoor	Short term
[78]	Barometer	Estimate altitude and altitude changes	Altitude, climate & weather, built environment, air velocity due to motion, and sensor accuracy	Compared barometric pressure data with topographical elevation data to localize and track vehicles	Transportation	Outdoor	Short and long term
[100]	Barometer and WiFi	Estimate altitude and altitude changes	Altitude, climate & weather, and sensor accuracy	Floor level identification by hybrid approach between barometer only and WiFi only method. Barometer-only approach uses crowd sensed barometer data for self-calibration and builds elevation map independently in each device	Ambulation	Indoor	Short term
[90]	Barometer, Accelerometer, and Gyroscope	Estimate altitude changes	Altitude and climate & weather	Improved activity recognition including VDA using barometer by considering behavioral rules and applying context in a two-step process	Ambulation	Indoor	Short term

[113]	Barometer, WiFi and Bluetooth	Estimate altitude and altitude changes	Altitude, climate & weather, and sensor accuracy	Used WiFi/ Bluetooth beacon to localize the user and recorded the respective pressure as reference pressure for that floor. Any change in elevation is then used to identify the floor level	Ambulation	Indoor	Short term
[91]	Barometer, Accelerometer, Gyroscope, Magnetometer, and Foot pressure	Estimate altitude change	Altitude	Activity recognition including VDA for better estimation of elderly physical activity	Ambulation	Indoor	Short term
[83]	Barometer and Accelerometer	Estimate altitude changes	Altitude	Low-power fall detection for long-term monitoring	Ambulation	Indoor and outdoor	Short and long term
[74]	Barometer	Detect door open/close in building and estimate altitude changes	Altitude, climate & weather, and built environment	Detect door open/close to monitor building activities and recognize VDA	Ambulation	Indoor and Outdoor	Short and long term
[114]	Barometer, Accelerometer, Gyroscope, Magnetometer, and WiFi	Estimate altitude and altitude changes	Altitude	3D indoor localization	Ambulation	Indoor	Short term
[87]	Barometer	Detect gait patterns and estimate altitude changes	Altitude	Step detection and activity recognition including VDA using barometer	Ambulation	Indoor	Short term
[84]	Barometer	Estimate altitude and altitude changes	Altitude, built environment, and sensor accuracy	Studied the different factors that affect barometric pressure in the built environment. Estimate indoor altitude.	Ambulation	Indoor	Short term
[110]	Barometer, Accelerometer, Gyroscope, Magnetometer, WiFi and microphone	Estimate altitude changes	Altitude	Determine location semantics such as restroom, desk, elevator, etc. using sensor fusion	Ambulation	Indoor and outdoor	Short term
[77]	Barometer and GPS	Detect vehicle patterns	Altitude, climate & weather, built environment, and air velocity during motion	Use the effect of elevation changes in roads and air velocity due to motion to detect the motion state of a vehicle and help identify traffic congestion	Transportation	Outdoor	Long term
[99]	Barometer	Estimate altitude and altitude changes	Altitude, climate & weather, and sensor accuracy	Calibration of wearable barometers using crowd-sourcing to enable floor localization. No knowledge of building or additional infrastructure is required	Ambulation	Indoor	Long term
[108]	Barometer	Estimate altitude and altitude changes	Altitude, climate & weather, built environment, air velocity during motion, and measurement accuracy	Recommendations to build indoor localization from reference pressure	Ambulation	Indoor	Long term
[28]	Barometer	Estimate altitude changes	Altitude, climate & weather, built environment, and sensor accuracy	Activity recognition including VDA using only barometer and comparison with accelerometer-only and GPS-only approaches	Ambulation and transportation	Indoor and outdoor	Short term
[79]	Barometer	Detect vehicle patterns and altitude changes	Altitude, climate & weather, air velocity during motion, and sensor accuracy	Identify transportation modes and ambulation activities using barometer	Ambulation and transportation	Indoor and Outdoor	Short term

[66]	Barometer	Estimate altitude and altitude changes	Altitude, climate & weather, built environment, and sensor accuracy	Floor localization using reference pressure from multiple barometers in each floor	Ambulation	Indoor	Short term
[70]	Barometer, Accelerometer, Gyroscope, and Magnetometer	Estimate altitude changes	Altitude	Identify the mode of vertical transport	Ambulation	Indoor	Short term

4. Factors affecting barometric pressure

Atmospheric pressure is the force applied per unit area by a column of air above a specified area [115]. It is caused by the gravitational pull of air molecules to the earth's surface. Atmospheric pressure as measured by a barometer is also called the barometric pressure.

Local atmospheric pressure is affected by several factors. From a fundamental point of view, these factors include the atmosphere's fluid properties such as density, moisture content, temperature, and motion. Speaking more generally, we can attribute the change in local barometric pressure to more abstract factors such as climate and weather [116–118], air velocity during motion, altitude, and built environment, with intricate interplays between all these factors. The magnitudes of the resultant effects vary and the corresponding ranges can be quantified for specific circumstances. Several studies have attempted to quantify these effects and provide a rich understanding of the factors that influence barometric pressure.

Table 2. Literature related to factors affecting barometric pressure.

Factors	References
Climate and Weather	[28,68,69,78,79,85,99,100,104,108,116–118]
Built environment	[66,68,74,84,101,119–121]
Air velocity during motion	[77–79,107,122–124]
Sensor accuracy	[66,69,72,76,78,85,90,99,100,108,113]

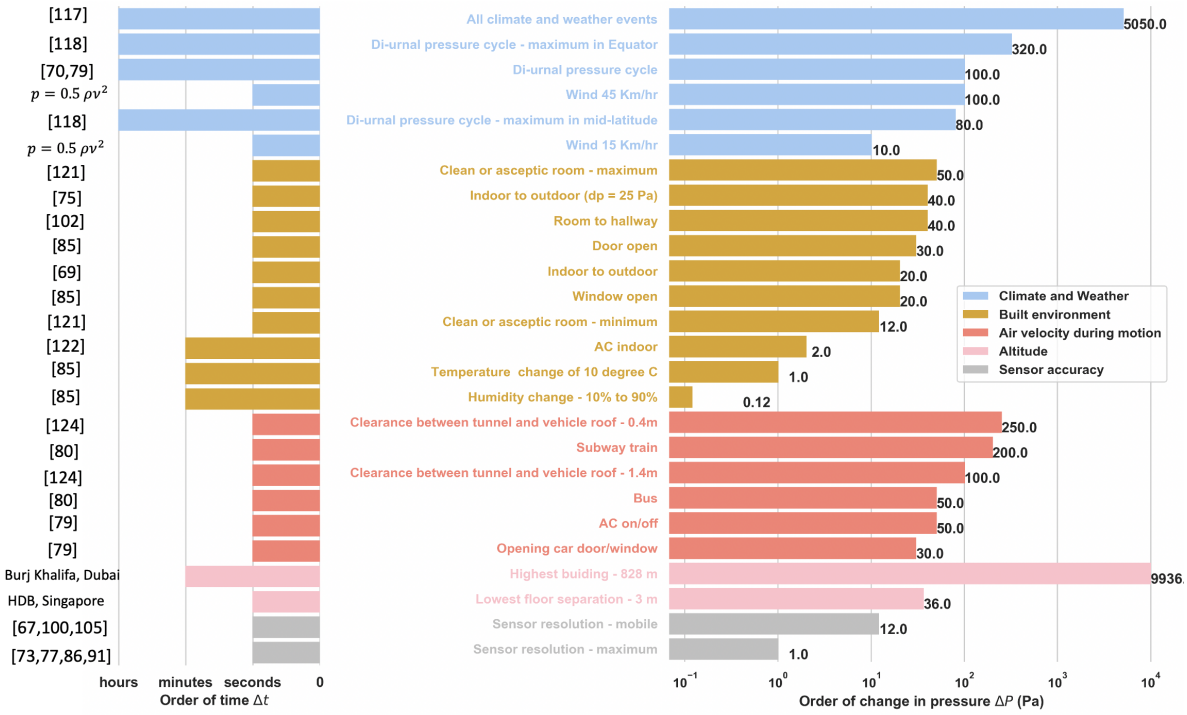


Figure 1. Orders of magnitude of changes in pressure and of the corresponding timescales for several factors influencing barometric pressure.

4.1. Climate and weather

The atmospheric pressure distribution on the planet is caused by the differential heating of the sun at different latitudes, which varies from the tropics to the polar regions [116]. Earth's tilt also contributes to the heating difference, as well as the nature of the surface being heated, i.e. ocean or land [116]. Moisture content in the air greatly affects the pressure distribution as the dry and moist air are heated differently. The differential heating hence produces high- and low-pressure regions on the planet. Due to seasonal differences in heating, the corresponding pressure distribution also changes seasonally [116].

The pressure distribution creates isobaric contours—i.e. the point along which atmospheric pressure is constant [116]. By a combination of the pressure differences in these isobaric regions and the Coriolis force generated by the earth's rotation, the air is moved from one place to another, creating wind. The resulting forces impact various scales, creating both the long-term climatic system of the planet and the short-term weather patterns observed locally.

It is very important to note that all weather patterns observed are caused by very small changes in pressure—i.e the maximum change in the sea-level atmospheric pressure never exceeds 5% of the absolute atmospheric pressure [116]. A gentle breeze (15 km/hr) creates a pressure difference of 10 Pa and a strong breeze (45 km/hr) creates 100 Pa difference [125]. Although the magnitude of wind factor is significant, their time scales are often slower than the scale of the human activity to be predicted. During the estimation of floor height, Liu et al. [104] showed that a windy day produces error in their estimation of floor height, while Sankaran et al. [79] found that a windy day produced no significant change in their prediction of mobility. Sanakaran et al. [79] further noted that neither wind nor rain had any significant impact in HAR. Similarly, Vanini et al. [28], while performing their VDA classification, found that neither cloudy nor rainy weather had any impact whatosever. Bao et al. [85] estimated the error caused by the wind and developed a model that takes into account the dynamic pressure change to remove this effect based on the wind speed. Figure 2 a shows an example of the effect of wind on barometer data: the pressure fluctuations when the sensor is exposed to wind are slightly but not significantly more erratic than the noise due to the sensor resolution.

Similar to surface heating, the upper part of the atmosphere is heated differently over the period of a day. The resulting diurnal temperature variations give rise to a diurnal pressure cycle (Fig 2 b) [117]. This behavior has been well documented since the 1830's [118], with a semi-diurnal cycle with two peaks around 9am–12pm and 9pm–12am, depending on the latitude [108]. In the tropics, the first late morning/afternoon cycle has the highest amplitude due to maximum heating during the day, while the second night cycle has a lesser amplitude given the reduced solar heating [117]. In the mid-latitude regions, these peaks are shown to have similar amplitudes for both cycles [117]. The highest pressure variations are reported closer to the equator with 320 Pa between maxima and minima, while the mid-latitude difference does not exceed 80 Pa [117]. Besides the periodical pressure variation, the absolute pressure also changes from day-to-day [108]. These changes are, however, prominent in mid-latitude regions ($\sim$ 600 Pa on average) while it is smaller in the tropic ($\sim$ 70 Pa on average).

Ho et al. analyzed pressure data from 2,309 U.S. cities and observed that these variations are less than 100 Pa per hour during 99% of the time [78], while Liu et al. [69] observed that they could exceed 100-Pa for intervals larger than one hour and remained stable over short intervals of less than one minute. The time scale of the diurnal pressure cycle is hence much larger than many human activity time scales, and these slow variations are not concerning for applications related to study and classification of human behavior [28,100]. Ho et al. [78] used reference pressure from nearby weather stations to alleviate this effect when identifying the correct elevation of a vehicle path. Bao et al. [85] modeled the first-order difference of this pressure cycle as a white Gaussian stochastic process. Other studies have focused on using relative pressure changes called differential pressure instead of the absolute pressure [68,99,100].

and weather.png

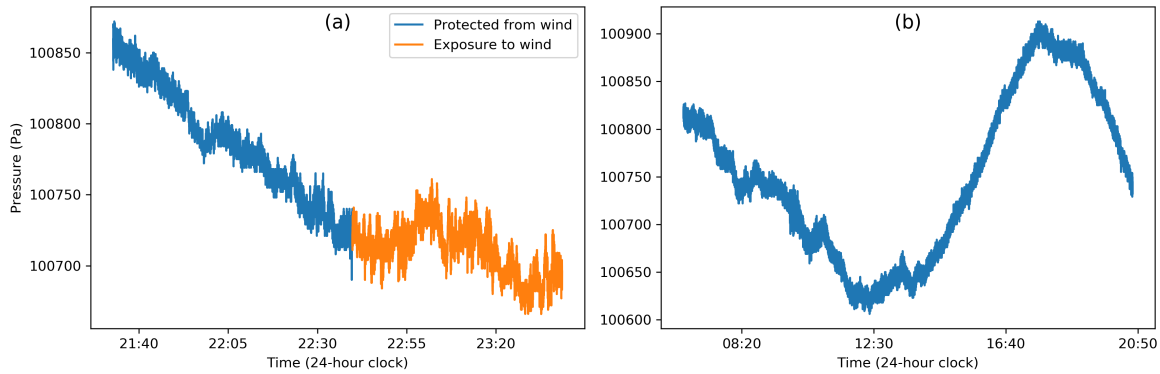


Figure 2. Climate and Weather (**a**) Diurnal pressure cycle in Singapore (**b**) Effect of wind. Recorded by custom-made device (barometer model - BMP280) with $\sim$ 1 Hz sampling rate.

4.2. Built environment

Ambient pressure can be controlled in an enclosed space using mechanical systems like Heating, Ventilation, and Air-conditioning (HVAC) systems [119]. Absolute and relative barometric pressure can thus be affected by these control systems. Buildings are positively pressurized compared to the exterior so as to have an outflow of air [120]. The magnitude of pressure differences is recommended by architects and regulatory authorities based on the function of the space. A minimum of 2.5 Pa is required for general living spaces, while a clean or aseptic isolation room is kept in a pressure difference of 12 $\sim$ 50 Pa to avoid contamination from outside.

Lstiburek et al. [121] list the four types of pressure field experienced by a building: 1. exterior field—outside a building, 2. interior field—inside a building room, corridors, stairwells, etc., 3. interstitial field—building cavities, and 4. air conveyance system field—air supply, heating, exhaust systems, etc. The temperature, moisture, and pressure inside a building hence fluctuate over the day by the interaction of these pressure fields caused by the building structure, climate & weather, and the mechanical systems inside the structure [121]. Bollmeyer et al. [84] observed that temperature and

humidity changes in a room have very little impact on barometric pressure. For instance, a temperature change of 10 degrees Celsius causes a ± 1 Pa change, while a humidity change from 10% to 90% creates a pressure difference of less than 0.12 Pa.

Muralidharan et al. [68] observed that the type of building space (tall, short, narrow and/or wide) and building pressurization also have little effects on barometric pressure measurement. They recorded pressure differences of less than 20 Pa even across multiple days. Xia et al. [66] similarly found no significant effects due to air-conditioning in their prediction of floor location.

Even if HVAC systems and the built environment have little effects on HAR, the transition between indoor and outdoor has been shown to produce noticeable pressure changes. Wu et al. [74] found that a constant pressure difference of 25 Pa between the interior and exterior of a building creates a pressure difference of $20 \sim 40$ Pa measured by barometer integrated to smartphones when carried during a door opening. Similarly, Bollmeyer et al. [84] found a 30 Pa jump when a door is opened and a 20 Pa jump when a window is opened. Lstiburek et al. [121] showed in 2002 that indoor air-conditioning can lead to pressure changes of approximately 2 Pa. More recently, Xu et al. [101] measured pressure differences between a room and the exterior of approximately 40 Pa.

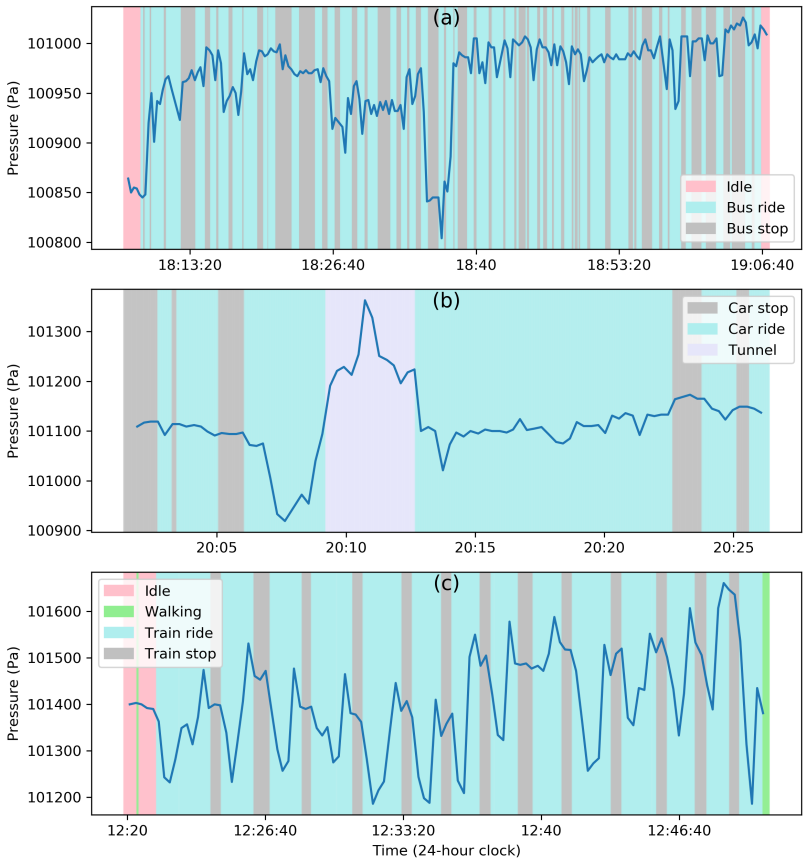
4.3. Air velocity during motion

Vehicles like cars and buses are in quasi-equilibrium with their environment due to the vents and ducts allowing the airflow in. This means that the barometric pressure inside a vehicle is very close to the exterior pressure. Note that the term 'exterior' denotes the air pressure in the immediate vicinity of the vehicle and not the ambient pressure far from it, which could be drastically different. This is due to the fact that ambient pressure is increased by the vehicle's motion near its surface where the dynamic pressure increases and the static pressure falls. The stagnation pressure on the surface caused by stopping the airflow near the surface produces a pressure distribution across the vehicle. This, in turn, creates pressure fluctuations inside the vehicle whenever its motion changes. However, this effect is transient and a quasi-equilibrium is reached quickly between interior and exterior. Figures 3a and 3b illustrate this behavior when a barometer is carried by a human subject during a bus and car ride respectively, where limited pressure fluctuations (~ 50 Pa) are observed.

On the other hand, the transition between stationary and moving vehicle can be quite noticeable. Ho et al. [78] found that the opening of a door/window during driving creates pressure changes of up to 30 Pa. During a car ride, they showed that switching the air-conditioning on and off created a pressure difference of 50 Pa [78]. It is very challenging to attribute it to climate-control system alone as the air-conditioning also brings in ventilated fresh air from the outside. However, Dimri et al. [77] observed that although there is a range of pressure jumps between different driving conditions (window open/closed, door open/closed, and AC on/off), this did not affect the prediction of whether a vehicle was stationary or in motion. This shows that during vehicle motion, air velocity can substantially determinate the pressure jumps more than the vehicle environment itself. More importantly, the pressure fluctuations experienced by the vehicle during its motion are predominant. This is shown in Fig. 3 c, where successive accelerations and decelerations of the train create significant pressure drops and rises respectively when it leaves and approaches a stop.

This effect can be severely amplified by the built environment such as tunnels for instance. Vehicles passing through a tunnel experience a "piston effect", where air is pulled inside the tunnel as the air is pushed back by the vehicle in motion [122,126]. This is shown in Figure 3b, where the car entering a tunnel leads to a drastic change of more than 200 Pa in the pressure measured inside the car. This effect has been shown to create a train of compression waves throughout the tunnel similar to sonic booms [123]. Sankaran et al. [79] showed that the pressure fluctuations during underground subway rides can exceed 200 Pa compared to a bus ride that shows fluctuations of ~ 50 Pa. Barnes et al. [124] analyzed road vehicle passage through tunnels in the Boston metropolitan area and found that the smaller the clearance between vehicle top and the tunnel roof, the higher the negative pressure drop on the sensor fixed to the tunnel roof, measuring a drop of 100 to 250 Pa for a clearance of 1.4 m

to 0.4 m. During subway rides, we can clearly distinguish between a train stop and motion [79] (see also Figure 3c). By combining this behavior with relative elevation data of train stations, Hyuga et al. [107] used the pressure jumps to estimate the location of a user during a subway ride.



velocity during motion.png

Figure 3. Illustration of the effect of air velocity during motion (**a**) Bus ride (**b**) Car ride and the effect of built environment (Tunnel) (**c**) Subway train ride. Each panel shows the effect of air velocity during motion on the barometric pressure, with different modes of transport showing different types of changes. Subway train rides yield the highest changes in magnitude (~ 200 Pa), while bus and car rides show relatively smaller amplitude changes (~ 50 Pa), except when a car is entering a tunnel. The panels also show the effect of elevation changes during travel. In panel (**a**), there is a fall and rise in pressure around $18:35$, corresponding to a climb and descent on the road path. Similarly, a drop and rise in pressure is observed in panel (**b**), where the car climbed and descended on an elevated bridge just before entering a tunnel. In panel (**c**), the acceleration of the train as it leaves the stop creates a sudden pressure drop, and a rise in pressure is subsequently observed as it approaches a stop, followed by a small dip in pressure as the train comes to equilibrium with the station environment, thus creating a repeating pressure pattern. Data was recorded by carrying a custom-made device (barometer model - BMP280) in different transport modes with a sampling rate ~ 0.06 Hz.

4.4. Altitude

Atmospheric pressure falls as we travel vertically upward above the earth's surface. This is due to the earth's gravitational pull of air molecules to the surface, which gives rise to a pressure gradient equals to $-\rho g$, where ρ is the air density and g is the local acceleration of gravity. As a consequence, the rate of change of altitude with pressure is almost linear near the earth's surface while it is almost exponential at higher altitudes when taking into account the variations of the air density with pressure and temperature [115]. This is again due to gravity which is stronger near the earth's surface combined with the fact that air molecules in lower atmosphere are compressed by the air molecules above

them [127]. For all purposes involving human activity under 10 km altitude above sea-level, it is safe to assume a linear relationship with altitude that typically shows a pressure decrease of 115 Pa per 10 meters climb [115]. As an illustration of the magnitude of the effect in the context of human activities, Figure 4 shows the barometric pressure change due to change in elevation through different vertical mobility modes such as elevator, escalator, and stairs.

Pressure-altitude relation: The pressure-altitude relationship can be derived from the fundamental equation for fluids at rest [128]. Assuming an incompressible fluid in isothermal conditions, the change in elevation is given by

$$z_2 - z_1 = -\frac{p_2 - p_1}{\gamma}, \tag{1}$$

where $\gamma = \rho g$ is the specific weight of air with density $\rho = 1.225\ \mathrm{kg/m^3}$ and acceleration due to gravity $g = 9.81\ \mathrm{m/s^2}$ at standard sea-level conditions. This pressure-altitude elevation holds with negligible errors as long as the elevation under study is less than 10 km from sea-level [128], which is the case in most studies.

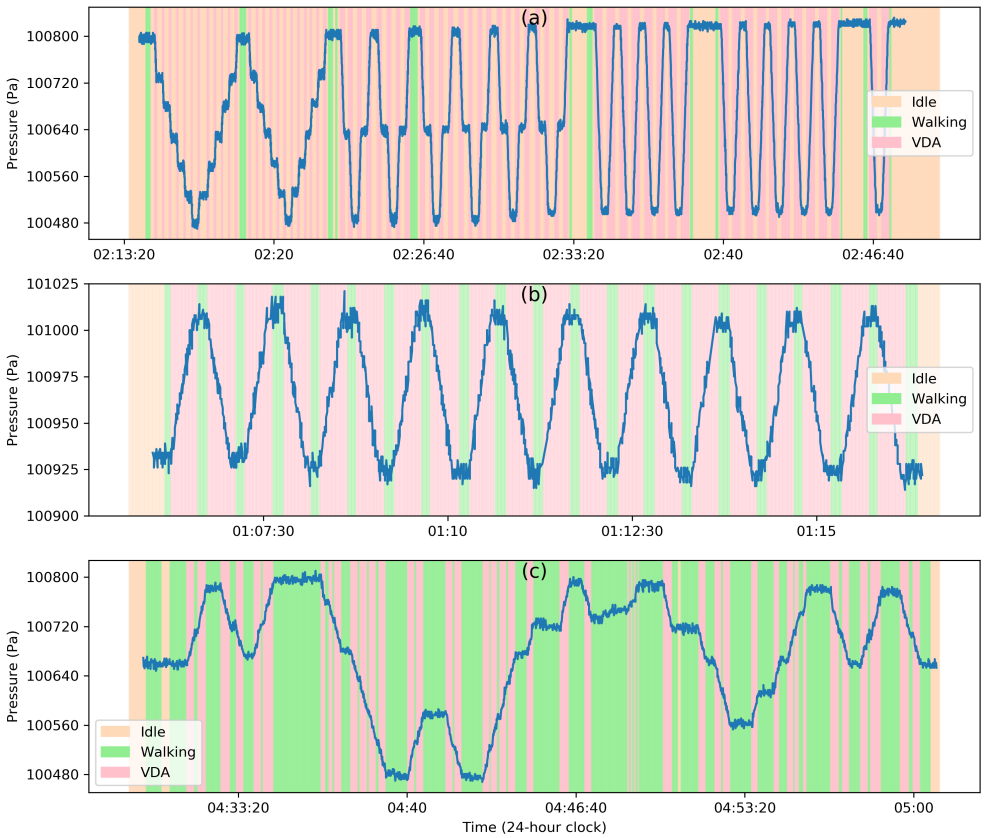


Figure 4. Effect of variations of altitude during human activity and motion. (**a**) Elevator (**b**) Escalator (**c**) Stairs. Data was collected by carrying a mobile device with a sampling rate $\sim$ 1 Hz on different modes of vertical mobility. For panel (**a**), the elevator was intentionally stopped at each floor in the first part of the data collection, to show the ability to distinguish single floor changes. In the second part, only one stop was made between the first and last floor. Finally, the last part of the data correspond to an uninterrupted elevator ride between the first and last floor. The data in panel (**b**) was collected by continuously climbing and descending on the same escalator, and the data in panel (**c**) was collected while using stairs. The escalator climb and descend in panel (**c**) corresponds to an average pressure difference of 80.7 Pa with a standard deviation of 3 Pa, showing the accuracy in recording relative pressure changes. Moreover, the relative pressure of 80 Pa corresponds to a height of 6.6 meters according to Eq. (1), close to the measured height of 7.3 meters and within the sensor resolution of $\pm$1 meter.

4.5. Sensor accuracy

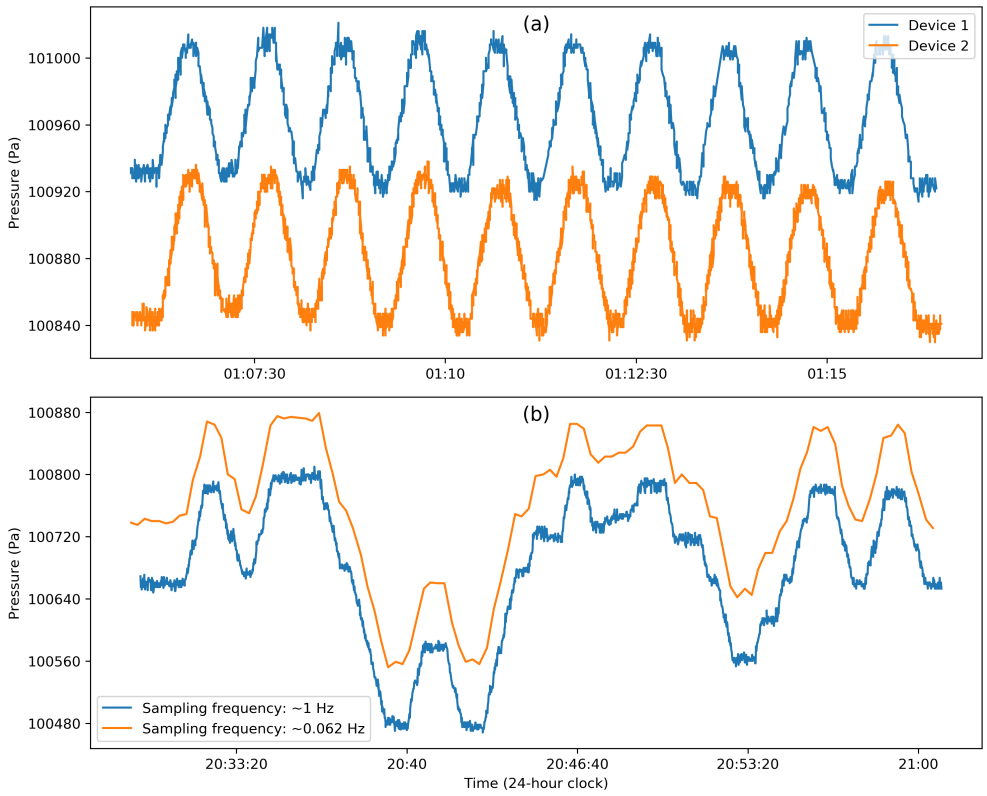
The quality of measurement of barometric pressure is limited by the sensor's accuracy. Both absolute and relative barometric pressure can change between devices due to differences in sensors and their characteristics. Here, the ensuing measurement errors are defined as caused by such inherent limitations of the sensor and not due to other factors, such as the environmental ones discussed previously [72,85].

Device dependency: The device dependency is introduced to account for differences between devices and software platforms [66,99,100,108,113], manufacturing inconsistencies, and inappropriate calibration by the manufacturer [100]. Figure 5-a illustrates how the time series of barometric pressure readings from two devices can differ. Absolute barometric pressure need thus to be calibrated between several devices for comparison [66]. This can be done before deployment or performed actively by using a reference pressure from nearby weather stations [85,108], building or floor level [66]. For instance, Ye et al. [99] used active peer-to-peer calibration when users detect each other and use the encounter network to calibrate all the devices. It is thus difficult or impossible to use barometers to measure absolute atmospheric pressure accurately without careful calibration, several studies have shown that it is possible to produce consistent relative pressure measurements [69,99,100,113]. The relative pressure however is also affected by the sensor's resolution, drift and noise.

Sensor resolution: The accuracy of the barometer is dependent on the built-in resolution of the sensor. Barometers embedded in mobile devices have generally a relative accuracy of ± 10 Pa [66,99,104], while commercially available high-resolution sensors can reach an accuracy of ± 1 Pa [72,76,85,90]. Sensor resolution is also affected by the measurement errors caused by noise. Haque et al. [72] used Allan Deviation (ADEV), a time domain analysis, to estimate the non-stationary errors of four different barometer models and listed the random noise processes that are dominant for a given observation period.

Sensor drift: Some sensors exhibit a drift in time due to faulty manufacturing or old age. Ho et al. [78] found this to be a temporary drift with a non-Gaussian distribution, and were able to remove it by modeling the noise as an Ohnstein–Uhlenbeck diffusion process—a process that pushes the drift towards its mean or center.

Sampling frequency: the recording frequency determines the completeness of the data. Weather stations generally send out data every hour, while mobile barometers embedded in mobile devices can be designed to output at a rate of $1 \sim 20$ Hz [76,79,82,83,92,94,104,114] or higher [67,89,105]. Depending on the activity to be recognized, this sampling frequency should be set appropriately to capture the actual time scale of the activity. As an illustration, Figure 5-b shows the time series of barometric pressure recorded by two devices with different sampling rates - 1 Hz and 0.06 Hz. It shows that altitude might not be accurately estimated during certain periods if the sampling rate is not high enough.



accuracy.png

Figure 5. Sensor accuracy (**a**) Device dependency: Two mobile phones were simultaneously carried by a human subject on an escalator to record the barometric pressure at $\sim$ 1 Hz sampling rate. The absolute pressure measured by each device is significantly different, while the relative pressure is practically constant. (**b**) Effect of sampling frequency: A mobile phone and a custom-built device were simultaneously carried by a human subject on stairs. They were both embedded with the same MEMS barometer model BMP280 but with different sampling rates, $\sim$ 1 Hz and $\sim$ 0.062 Hz respectively. This panel shows how the sampling rate affects the detection of altitude changes.

5. Future research

Today, barometers are found in almost (if not all) wearable devices and smartphones. The vast breadth of applications listed in this review underscores the tremendous potential use in extracting barometric pressure data on a massive scale. Some attempts with limited scope are reported in Table 1. However, the systematic use of barometer data could be envisioned at large scale and on long time scales as a tool to study some aspects of the behavior of large populations of humans (or other living creatures) in their free-living environment, similarly to what has been done with mobile phone call detail records for studies of communications and mobility.

Tracking human activities inevitably leads to privacy issues. Anonymity of individuals cannot be guaranteed even with coarse spatial and temporal resolutions of the collected data [129]. Re-identification of individuals from seemingly anonymous data has been shown to be effectively performed due to unique signatures of human mobility [129,130]. This issue arises as well with the use of barometers, where re-identification of human subjects could be possible using the tracking of altitude changes during the start and end of each day. In effect, barometer can be used to perform the so-called last-mile tracking that increases the spatial resolution from a block to a floor. This is a particularly pronounced problem in highly vertical cities, and a proper framework to protect the privacy should take into account the potential use of barometer data when tracking human activity.

Furthermore, barometers are increasingly used as a practical complement to other sensors for tracking human activities. Methods that enable sensor data fusion of barometric signals to other sensory data need to evolve to fully realize the barometers' full potential.

The application of barometers to study gait patterns, step count, environmental monitoring, building monitoring, vehicle tracking, and health monitoring should be more widely explored. For instance, when aiming at the detection of VDA, barometric signal data need to be considered not only to recognize altitude changes but also to determine the mode of vertical transport (stairs climbing, slope, escalator or elevator ride). In studying epidemic disease propagation for example, it makes a significant difference to recognize whether the subject is in an elevator (closed space) or on an escalator (open space).

Table 1 also shows that for many applications, not all the factors that can influence pressure are always considered, even after taking into consideration the limited scope of these studies. These factors are not always fully understood and their magnitude is not universally agreed upon due to the wide range of conditions under which these experiments are performed (see Fig. 1). It is thus crucial to understand and quantify all the factors affecting the barometric pressure when working on a particular problem or application related to human activity tracking and recognition. Some of these effects may be irrelevant, while others might impair our ability to properly identify patterns of activity from the sensed data. Section 4 of the present review endeavors to move in this direction by reviewing the fundamental properties of atmospheric pressure and inspecting their interaction with several environmental conditions that arise when a barometer is carried by a human. It also brings together a range of studies from different fields of science and engineering that have contributed to improve the understanding of the factors influencing atmospheric and barometric pressure and to quantify their respective magnitude (see Fig. 1).

Author Contributions: Conceptualization: R.B.; methodology: R.B.,A.M.; writing–original draft preparation: R.B., A.M.; writing–review and editing: R.B.,A.B.,B.C.; supervision: R.B.,A.B.

Funding: This research was supported by an SUTD grant (Cities Sector: PIE-SGP-CTRS-1803).

Acknowledgments: We would like to thank Dr. Elias J. Willemse for fruitful discussions and comments. We also would like to thank Dr. Bige Tunçer and her research team for assistance with barometric sensors and guidance on data collection. A.M. is supported by an MOE-SUTD PhD fellowship.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

MEMS	Micro-ElectroMechanical System
GPS	Global Positioning System
ADL	Activities of Daily Living
UAV	Unmanned Aerial Vehicle
IoT	Internet of Things
IMU	Inertial Measurement Unit
Pa	Pascal (unit)
Hz	Hertz (unit)
PCA	Principal Component Analysis
VDA	Vertical Displacement Activities
SMOTE	Synthetic Minority Over-sampling Technique
BMI	Body Mass Index
ML	Machine Learning
RFID	Radio Frequency IDentification
FIR	Finite Impulse Response filters
IIR	Infinite Impulse Response filters
DP	Differential Pressure
HAR	Human Activity Recognition
SVM	Support Vector Machine
LSTM	Long Short Term Memory networks
HMM	Hidden Markow Model
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
DTW	Dynamic Time Warping
HVAC	Heating, Ventilation, and Air-conditioning system
AC	Air-conditioning system
ADEV	Allen Deviation

References

1. Magie, W.F. *A Source Book in Physics*; Harvard University Press, 1969.
2. Pascal, B.; Barry, F.; Spiers, I.H.B.; Spiers, A.G.H.; Stevin, S.; Galilei, G.; Torricelli, E.; others. *The Physical Treatises of Pascal: The Equilibrium of Liquids and the Weight of the Mass of the Air*; MPublishing, University of Michigan Library, 1937. acls humanities e-book.
3. Middleton, W.E. *The History of the Barometer*; Baros, 1994.
4. Figuier, L.; Gautier, É. *L'Année Scientifique et Industrielle*; Vol. 5, Hachette et cie., 1861.
5. Five billion Bosch MEMS sensors. Available online: https://www.bosch-presse.de/pressportal/de/en/five-billion-bosch-mems-sensors-42857.html. (accessed on 15/08/2020).
6. Barometric Pressure Sensors: The Design Engineer's Guide: Avnet Abacus. Available online: https://www.avnet.com/wps/portal/abacus/solutions/technologies/sensors/pressure-sensors/media-types/barometric/. (accessed on 15/08/2020).
7. Lara, O.D.; Labrador, M.A. A survey on human activity recognition using wearable sensors. *IEEE communications surveys & tutorials* **2013**, *15*, 1192–1209.
8. Accelerometer - Research Article from World of Invention. Available online: http://www.bookrags.com/research/accelerometer-woi/#gsc.tab=0. (accessed on 15/08/2020).
9. Del Rosario, M.B.; Redmond, S.J.; Lovell, N.H. Tracking the evolution of smartphone sensing for monitoring human movement. *Sensors* **2015**, *15*, 18901–18933.
. Parviainen, J.; Kantola, J.; Collin, J. Differential barometry in personal navigation. 2008 IEEE/ION Position, Location and Navigation Symposium. IEEE, 2008, pp. 148–152.
10. Janidarmian, M.; Fekr, A.R.; Radecka, K.; Zilic, Z. A comprehensive analysis on wearable acceleration sensors in human activity recognition. *Sensors (Switzerland)* **2017**, *17*. doi:10.3390/s17030529.

11. Twomey, N.; Diethe, T.; Fafoutis, X.; Elsts, A.; McConville, R.; Flach, P.; Craddock, I. A Comprehensive Study of Activity Recognition Using Accelerometers. *Informatics* **2018**, *5*, 27. doi:10.3390/informatics5020027.
12. Shoaib, M.; Bosch, S.; Durmaz Incel, O.; Scholten, H.; Havinga, P.J. *Fusion of smartphone motion sensors for physical activity recognition*; Vol. 14, 2014; pp. 10146–10176. doi:10.3390/s140610146.
13. Chung, S.; Lim, J.; Noh, K.J.; Kim, G.; Jeong, H. Sensor data acquisition and multimodal sensor fusion for human activity recognition using deep learning. *Sensors (Switzerland)* **2019**, *19*. doi:10.3390/s19071716.
14. Willetts, M.; Hollowell, S.; Aslett, L.; Holmes, C.; Doherty, A. Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Scientific Reports* **2018**, *8*, 1–10. doi:10.1038/s41598-018-26174-1.
15. Yang, X.; Stewart, K.; Tang, L.; Xie, Z.; Li, Q. A review of GPS trajectories classification based on transportation mode. *Sensors (Switzerland)* **2018**, *18*, 1–20. doi:10.3390/s18113741.
16. Huang, H.; Cheng, Y.; Weibel, R. Transport mode detection based on mobile phone network data: A systematic review. *Transportation Research Part C: Emerging Technologies* **2019**, *101*, 297–312. doi:10.1016/j.trc.2019.02.008.
17. Mun, M.; Estrin, D.; Burke, J. Parsimonious mobility classification using GSM and WiFi traces. *Proc. of the Fifth Workshop on Embedded Networked Sensors (HotEmNets)* **2008**, pp. 1–5.
18. Sapiezynski, P.; Stopczynski, A.; Gatej, R.; Lehmann, S. Tracking human mobility using WiFi signals. *PLoS ONE* **2015**, *10*, 1–11. doi:10.1371/journal.pone.0130824.
19. Keramat Jahromi, K.; Zignani, M.; Gaito, S.; Rossi, G.P. Simulating human mobility patterns in urban areas. *Simulation Modelling Practice and Theory* **2016**, *62*, 137–156. doi:10.1016/j.simpat.2015.12.002.
20. Jiang, S.; Ferreira, J.; Gonzalez, M.C. Activity-Based Human Mobility Patterns Inferred from Mobile Phone Data: A Case Study of Singapore. *IEEE Transactions on Big Data* **2016**, *3*, 208–219. doi:10.1109/tbdata.2016.2631141.
21. Prelipcean, A.C.; Gidófalvi, G.; Susilo, Y.O. Transportation mode detection–an in-depth review of applicability and reliability. *Transport Reviews* **2017**, *37*, 442–464. doi:10.1080/01441647.2016.1246489.
22. Kunze, K.; Lukowicz, P. Sensor placement variations in wearable activity recognition. *IEEE Pervasive Computing* **2014**, *13*, 32–41. doi:10.1109/MPRV.2014.73.
23. Ustev, Y.E.; Durmaz Incel, O.; Ersoy, C. User, device and orientation independent human activity recognition on mobile phones **2013**. pp. 1427–1436. doi:10.1145/2494091.2496039.
24. Khan, A.M.; Lee, Y.K.; Lee, S.Y.; Kim, T.S. Human activity recognition via an accelerometer-enabled-smartphone using Kernel Discriminant Analysis. *2010 5th International Conference on Future Information Technology, FutureTech 2010 - Proceedings* **2010**, pp. 1–6. doi:10.1109/FUTURETECH.2010.5482729.
25. Chen, Z.; Zhu, Q.; Soh, Y.C.; Zhang, L. Robust Human Activity Recognition Using Smartphone Sensors via CT-PCA and Online SVM. *IEEE Transactions on Industrial Informatics* **2017**, *13*, 3070–3080. doi:10.1109/TII.2017.2712746.
26. Pannurat, N.; Thiemjarus, S.; Nantajeewarawat, E.; Anantavrasilp, I. Analysis of optimal sensor positions for activity classification and application on a different data collection scenario. *Sensors (Switzerland)* **2017**, *17*. doi:10.3390/s17040774.
27. Maurer, U.; Smailagic, A.; Siewiorek, D.P.; Deisher, M. Activity recognition and monitoring using multiple sensors on different body positions. International Workshop on Wearable and Implantable Body Sensor Networks (BSN'06). IEEE, 2006, pp. 4–pp.
28. Vanini, S.; Faraci, F.; Ferrari, A.; Giordano, S. Using barometric pressure data to recognize vertical displacement activities on smartphones. *Computer Communications* **2016**, *87*, 37–48.
29. Jerri, A.J. The Shannon sampling theorem—Its various extensions and applications: A tutorial review. *Proceedings of the IEEE* **1977**, *65*, 1565–1596.
30. Khan, A.; Hammerla, N.; Mellor, S.; Plötz, T. Optimising sampling rates for accelerometer-based human activity recognition. *Pattern Recognition Letters* **2016**, *73*, 33–40. doi:10.1016/j.patrec.2016.01.001.
31. Yan, Z.; Subbaraju, V.; Chakraborty, D.; Misra, A.; Aberer, K. Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach. *Proceedings - International Symposium on Wearable Computers, ISWC* **2012**, pp. 17–24. doi:10.1109/ISWC.2012.23.

32. Feng, T.; Timmermans, H.J. Transportation mode recognition using GPS and accelerometer data. *Transportation Research Part C: Emerging Technologies* **2013**, *37*, 118–130. doi:10.1016/j.trc.2013.09.014.
33. Shen, L.; Stopher, P.R. Should we change the rules for trip identification for GPS travel records? *Australasian Transport Research Forum* **2013**, pp. 1–11.
34. Münzner, S.; Schmidt, P.; Reiss, A.; Hanselmann, M.; Stiefelhagen, R.; Dürichen, R. CNN-based sensor fusion techniques for multimodal human activity recognition **2017**. pp. 158–165. doi:10.1145/3123021.3123046.
35. Blanke, U.; Schiele, B. Remember and transfer what you have learned-recognizing composite activities based on activity spotting. International Symposium on Wearable Computers (ISWC) 2010. IEEE, 2010, pp. 1–8.
36. Helaoui, R.; Niepert, M.; Stuckenschmidt, H. Recognizing interleaved and concurrent activities: A statistical-relational approach. 2011 IEEE International Conference on Pervasive Computing and Communications (PerCom). IEEE, 2011, pp. 1–9.
37. Cleland, I.; Donnelly, M.P.; Nugent, C.D.; Hallberg, J.; Espinilla, M.; Garcia-Constantino, M. Collection of a Diverse, Realistic and Annotated Dataset for Wearable Activity Recognition. *2018 IEEE International Conference on Pervasive Computing and Communications Workshops, PerCom Workshops 2018* **2018**, pp. 555–560. doi:10.1109/PERCOMW.2018.8480322.
38. Chen, Y.; Shen, C. Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition. *IEEE Access* **2017**, *5*, 3095–3110. doi:10.1109/ACCESS.2017.2676168.
39. Thomas Plötz, N.Y.H. Feature Learning for Activity Recognition in Ubiquitous Computing **2011**. pp. 1729–1734. doi:10.5591/978-1-57735-516-8/IJCAI11-290.
40. Garcia-Ceja, E.; Galván-Tejada, C.E.; Brena, R. Multi-view stacking for activity recognition with sound and accelerometer data. *Information Fusion* **2018**, *40*, 45–56. doi:10.1016/j.inffus.2017.06.004.
41. Jordao, A.; Nazare, A.C.; Sena, J.; Schwartz, W.R. Human Activity Recognition Based on Wearable Sensor Data: A Standardization of the State-of-the-Art **2018**. pp. 1–11, [1806.05226].
42. Murad, A.; Pyun, J.Y. Deep recurrent neural networks for human activity recognition. *Sensors (Switzerland)* **2017**, *17*. doi:10.3390/s17112556.
43. De-La-Hoz-Franco, E.; Ariza-Colpas, P.; Quero, J.M.; Espinilla, M. Sensor-based datasets for human activity recognition–A systematic review of literature. *IEEE Access* **2018**, *6*, 59192–59210.
44. Wang, Z.; Jiang, M.; Hu, Y.; Li, H. An incremental learning method based on probabilistic neural networks and adjustable fuzzy clustering for human activity recognition by using wearable sensors. *IEEE Transactions on Information Technology in Biomedicine* **2012**, *16*, 691–699. doi:10.1109/TITB.2012.2196440.
45. Banos, O.; Damas, M.; Pomares, H.; Prieto, A.; Rojas, I. Daily living activity recognition based on statistical feature quality group selection. *Expert Systems with Applications* **2012**, *39*, 8013–8021. doi:10.1016/j.eswa.2012.01.164.
46. Anguita, D. A Public Domain Dataset for Human Activity Recognition Using Smartphones **2015**. pp. 1–12.
47. Nazabal, A.; Garcia-Moreno, P.; Artes-Rodriguez, A.; Ghahramani, Z. Human Activity Recognition by Combining a Small Number of Classifiers. *IEEE Journal of Biomedical and Health Informatics* **2016**, *20*, 1342–1351. doi:10.1109/JBHI.2015.2458274.
48. Lara, Ó.D.; Prez, A.J.; Labrador, M.A.; Posada, J.D. Centinela: A human activity recognition system based on acceleration and vital sign data. *Pervasive and Mobile Computing* **2012**, *8*, 717–729. doi:10.1016/j.pmcj.2011.06.004.
49. Bao, L.; Intille, S.S. Activity Recognition from User-Annotated Acceleration Data BT - UbiComp 2002: Ubiquitous Computing. *UbiComp 2002: Ubiquitous Computing* **2004**, *3001*, 1–17.
50. Bota, P.; Silva, J.; Folgado, D.; Gamboa, H. A Semi-Automatic Annotation Approach for Human Activity Recognition. *Sensors (Basel, Switzerland)* **2019**, *19*, 1–23. doi:10.3390/s19030501.
51. Inoue, M.; Inoue, S.; Nishida, T. Deep recurrent neural network for mobile human activity recognition with high throughput. *Artificial Life and Robotics* **2018**, *23*, 173–185. doi:10.1007/s10015-017-0422-x.
52. Guan, Y.; Ploetz, T. Ensembles of Deep LSTM Learners for Activity Recognition using Wearables **2017**. *1*, [1703.09370]. doi:10.1145/3090076.
53. Ermes, M.; Pärkkä, J.; Mäntyjärvi, J.; Korhonen, I. Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE Transactions on Information Technology in Biomedicine* **2008**. doi:10.1109/TITB.2007.899496.

54. Trung, K. Dealing with Imbalanced Data Sets for Human Activity Recognition Using Mobile Phone Sensors **2018**. *0*. doi:10.3233/978-1-61499-874-7-129.
55. Capela, N.A.; Lemaire, E.D.; Baddour, N.; Rudolf, M.; Goljar, N.; Burger, H. Evaluation of a smartphone human activity recognition application with able-bodied and stroke participants. *Journal of NeuroEngineering and Rehabilitation* **2016**, *13*, 1–10. doi:10.1186/s12984-016-0114-0.
56. Almaslukh, B.; Artoli, A.M.; Al-Muhtadi, J. A robust deep learning approach for position-independent smartphone-based human activity recognition. *Sensors (Switzerland)* **2018**, *18*. doi:10.3390/s18113726.
57. Nweke, H.F.; Teh, Y.W.; Alo, U.R.; Mujtaba, G. Analysis of Multi-Sensor Fusion for Mobile and Wearable Sensor Based Human Activity Recognition **2018**. pp. 22–26. doi:10.1145/3224207.3224212.
58. Mehrang, S.; Pietilä, J.; Korhonen, I. An activity recognition framework deploying the random forest classifier and a single optical heart rate monitoring and triaxial accelerometer wrist-band. *Sensors (Switzerland)* **2018**, *18*, 1–13. doi:10.3390/s18020613.
59. Stikic, M.; Larlus, D.; Ebert, S.; Schiele, B. Weakly supervised recognition of daily life activities with wearable sensors. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **2011**, *33*, 2521–2537. doi:10.1109/TPAMI.2011.36.
60. Incel, O.D.; Ozgovde, A. ARService: A Smartphone based Crowd-Sourced Data Collection and Activity Recognition Framework. *Procedia Computer Science* **2018**, *130*, 1019–1024. doi:10.1016/j.procs.2018.04.142.
61. Anjum, A.; Ilyas, M.U. Activity recognition using smartphone sensors. *2013 IEEE 10th Consumer Communications and Networking Conference (CCNC)* **2013**, pp. 914–919. doi:10.1109/ccnc.2013.6488584.
62. Sztyler, T.; Stuckenschmidt, H. On-body localization of wearable devices: An investigation of position-aware activity recognition. *2016 IEEE International Conference on Pervasive Computing and Communications, PerCom 2016* **2016**, pp. 1–9. doi:10.1109/PERCOM.2016.7456521.
63. Khan, A.M.; Lee, Y.K.; Lee, S.Y.; Kim, T.S. A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. *IEEE transactions on information technology in biomedicine* **2010**, *14*, 1166–1172.
64. Tam, D.; Huynh, G. Human Activity Recognition with Wearable Sensors. PhD thesis, 2008.
65. Lang, C.; Kaiser, S. Classifying Elevators and Escalators in 3D Pedestrian Indoor Navigation Using Foot-Mounted Sensors. 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2018, pp. 1–7.
66. Xia, H.; Wang, X.; Qiao, Y.; Jian, J.; Chang, Y. Using multiple barometers to detect the floor location of smart phones with built-in barometric sensors for indoor positioning. *Sensors* **2015**, *15*, 7857–7877.
67. Kronenwett, N.; Qian, S.; Mueller, K.; Trommer, G.F. Elevator and Escalator Classification for Precise Indoor Localization. 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2018, pp. 1–8.
68. Muralidharan, K.; Khan, A.J.; Misra, A.; Balan, R.K.; Agarwal, S. Barometric phone sensors: More hype than hope! Proceedings of the 15th Workshop on Mobile Computing Systems and Applications. ACM, 2014, p. 12.
69. Liu, M.; Li, H.; Wang, Y.; Li, F.; Chen, X. Double-Windows-Based Motion Recognition in Multi-Floor Buildings Assisted by a Built-In Barometer. *Sensors* **2018**, *18*, 1061.
70. Elhoushi, M.; Georgy, J.; Wahdan, A.; Korenberg, M.; Noureldin, A. Using portable device sensors to recognize height changing modes of motion. 2014 Ieee International Instrumentation and Measurement Technology Conference (I2mtc) Proceedings. IEEE, 2014, pp. 477–481.
71. Pipelidis, G.; Rad, O.R.M.; Iwaszczuk, D.; Prehofer, C.; Hugentobler, U. A novel approach for dynamic vertical indoor mapping through crowd-sourced smartphone sensor data. 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2017, pp. 1–8.
72. Haque, F.; Dehghanian, V.; Fapojuwo, A.O.; Nielsen, J. A Sensor Fusion-Based Framework for Floor Localization. *IEEE Sensors Journal* **2018**, *19*, 623–631.
73. Shen, X.; Chen, Y.; Zhang, J.; Wang, L.; Dai, G.; He, T. BarFi: Barometer-aided Wi-Fi floor localization using crowdsourcing. 2015 IEEE 12th International Conference on Mobile Ad Hoc and Sensor Systems. IEEE, 2015, pp. 416–424.
74. Wu, M.; Pathak, P.H.; Mohapatra, P. Monitoring building door events using barometer sensor in smartphones. Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 2015, pp. 319–323.

75. Leuenberger, K.; Gonzenbach, R.; Wiedmer, E.; Luft, A.; Gassert, R. Classification of stair ascent and descent in stroke patients. 2014 11th International Conference on Wearable and Implantable Body Sensor Networks Workshops. IEEE, 2014, pp. 11–16.
76. Bianchi, F.; Redmond, S.J.; Narayanan, M.R.; Cerutti, S.; Lovell, N.H. Barometric pressure and triaxial accelerometry-based falls event detection. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **2010**, *18*, 619–627.
77. Dimri, A.; Singh, H.; Aggarwal, N.; Raman, B.; Bansal, D.; Ramakrishnan, K. RoadSphygmo: Using barometer for traffic congestion detection. 2016 8th International Conference on Communication Systems and Networks (COMSNETS). IEEE, 2016, pp. 1–8.
78. Ho, B.J.; Martin, P.; Swaminathan, P.; Srivastava, M. From pressure to path: Barometer-based vehicle tracking. Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments. ACM, 2015, pp. 65–74.
79. Sankaran, K.; Zhu, M.; Guo, X.F.; Ananda, A.L.; Chan, M.C.; Peh, L.S. Using mobile phone barometer for low-power transportation context detection. Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems. ACM, 2014, pp. 191–205.
80. Sagawa, K.; Ishihara, T.; Ina, A.; Inooka, H. Classification of human moving patterns using air pressure and acceleration. 2002, pp. 1214–1219. doi:10.1109/iecon.1998.724274.
81. Bolanakis, D.E. Evaluating performance of MEMS barometric sensors in differential altimetry systems. *IEEE Aerospace and Electronic Systems Magazine* **2017**, *32*, 34–39.
82. Del Rosario, M.B.; Wang, K.; Wang, J.; Liu, Y.; Brodie, M.; Delbaere, K.; Lovell, N.H.; Lord, S.R.; Redmond, S.J. A comparison of activity classification in younger and older cohorts using a smartphone. *Physiological measurement* **2014**, *35*, 2269.
83. Wang, C.; Lu, W.; Narayanan, M.R.; Chang, D.C.W.; Lord, S.R.; Redmond, S.J.; Lovell, N.H. Low-power fall detector using triaxial accelerometry and barometric pressure sensing. *IEEE Transactions on Industrial Informatics* **2016**, *12*, 2302–2311.
84. Bollmeyer, C.; Esemann, T.; Gehring, H.; Hellbrück, H. Precise indoor altitude estimation based on differential barometric sensing for wireless medical applications. 2013 IEEE International Conference on Body Sensor Networks. IEEE, 2013, pp. 1–6.
85. Bao, X.; Xiong, Z.; Sheng, S.; Dai, Y.; Bao, S.; Liu, J. Barometer measurement error modeling and correction for UAH altitude tracking. 2017 29th Chinese Control And Decision Conference (CCDC). IEEE, 2017, pp. 3166–3171.
86. Sabatini, A.; Genovese, V. A sensor fusion method for tracking vertical velocity and height based on inertial and barometric altimeter measurements. *Sensors* **2014**, *14*, 13324–13347.
87. Ghimire, B.; Nickel, C.; Seitz, J. Pedestrian motion state classification using pressure sensors. 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2016, pp. 1–6.
88. Voleno, M.; Redmond, S.J.; Cerutti, S.; Lovell, N.H. Energy expenditure estimation using triaxial accelerometry and barometric pressure measurement. 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology. IEEE, 2010, pp. 5185–5188.
89. Moncada-Torres, A.; Leuenberger, K.; Gonzenbach, R.; Luft, A.; Gassert, R. Activity classification based on inertial and barometric pressure sensors at different anatomical locations. *Physiological measurement* **2014**, *35*, 1245.
90. Massé, F.; Gonzenbach, R.R.; Arami, A.; Paraschiv-Ionescu, A.; Luft, A.R.; Aminian, K. Improving activity recognition using a wearable barometric pressure sensor in mobility-impaired stroke patients. *Journal of neuroengineering and rehabilitation* **2015**, *12*, 72.
91. el Achkar, C.M.; Lenoble-Hoskovec, C.; Paraschiv-Ionescu, A.; Major, K.; Büla, C.; Aminian, K. Instrumented shoes for activity classification in the elderly. *Gait & posture* **2016**, *44*, 12–17.
92. Figueira, C.; Matias, R.; Gamboa, H. Body Location Independent Activity Monitoring. BIOSIGNALS, 2016, pp. 190–197.
93. Ejupi, A.; Galang, C.; Aziz, O.; Park, E.J.; Robinovitch, S. Accuracy of a wavelet-based fall detection approach using an accelerometer and a barometric pressure sensor. 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2017, pp. 2150–2153.
94. Monteiro, M.; Martí, A.C. Using smartphone pressure sensors to measure vertical velocities of elevators, stairways, and drones. *arXiv preprint arXiv:1607.00363* **2016**.

95. Nam, Y.; Park, J.W. Child activity recognition based on cooperative fusion model of a triaxial accelerometer and a barometric pressure sensor. *IEEE journal of biomedical and health informatics* **2013**, *17*, 420–426.
96. Loh, D.; Lee, T.J.; Zihajehzadeh, S.; Hoskinson, R.; Park, E.J. Fitness activity classification by using multiclass support vector machines on head-worn sensors. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2015, pp. 502–505.
97. Anastasopoulou, P.; Tansella, M.; Stumpp, J.; Shammas, L.; Hey, S. Classification of human physical activity and energy expenditure estimation by accelerometry and barometry. 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2012, pp. 6451–6454.
98. Kim, S.S.; Kim, J.W.; Han, D.S. Floor detection using a barometer sensor in a smartphone. 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2017.
99. Ye, H.; Gu, T.; Tao, X.; Lu, J. Scalable floor localization using barometer on smartphone. *Wireless Communications and Mobile Computing* **2016**, *16*, 2557–2571.
100. Zhao, F.; Luo, H.; Zhao, X.; Pang, Z.; Park, H. HYFI: Hybrid floor identification based on wireless fingerprinting and barometric pressure. *IEEE Transactions on Industrial Informatics* **2015**, *13*, 330–341.
101. Xu, Z.; Wei, J.; Zhu, J.; Yang, W. A robust floor localization method using inertial and barometer measurements. 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2017, pp. 1–8.
102. Kamiya, Y.; Gu, Y.; Kamijo, S. Indoor Positioning in Large Shopping Mall with Context based Map Matching. 2019 IEEE International Conference on Consumer Electronics (ICCE). IEEE, 2019, pp. 1–6.
103. Yi, S.; Mirowski, P.; Ho, T.K.; Pavlovic, V. Pose invariant activity classification for multi-floor indoor localization. 2014 22nd International Conference on Pattern Recognition. IEEE, 2014, pp. 3505–3510.
104. Liu, G.; Iwai, M.; Tobe, Y.; Matekenya, D.; Hossain, K.M.A.; Ito, M.; Sezaki, K. Beyond horizontal location context: measuring elevation using smartphone's barometer. Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication. ACM, 2014, pp. 459–468.
105. Sagawa, K.; Ishihara, T.; Ina, A.; Inooka, H. Classification of human moving patterns using air pressure and acceleration. IECON'98. Proceedings of the 24th Annual Conference of the IEEE Industrial Electronics Society (Cat. No. 98CH36200). IEEE, 1998, Vol. 2, pp. 1214–1219.
106. Kaiser, S.; Lang, C. Detecting elevators and escalators in 3d pedestrian indoor navigation. 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2016, pp. 1–6.
107. Hyuga, S.; Ito, M.; Iwai, M.; Sezaki, K. Estimate a user's location using smartphone's barometer on a subway. Proceedings of the 5th International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments. ACM, 2015, p. 2.
108. Li, B.; Harvey, B.; Gallagher, T. Using barometers to determine the height for indoor positioning. International Conference on Indoor Positioning and Indoor Navigation. IEEE, 2013, pp. 1–7.
109. Pipelidis, G.; Moslehi Rad, O.; Iwaszczuk, D.; Prehofer, C.; Hugentobler, U. Dynamic Vertical Mapping with Crowdsourced Smartphone Sensor Data. *Sensors* **2018**, *18*, 480.
110. Tachikawa, M.; Maekawa, T.; Matsushita, Y. Predicting location semantics combining active and passive sensing with environment-independent classifier. Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 2016, pp. 220–231.
111. Son, Y.; Oh, S. A barometer-IMU fusion method for vertical velocity and height estimation. 2015 IEEE SENSORS. IEEE, 2015, pp. 1–4.
112. Ohtaki, Y.; Susumago, M.; Suzuki, A.; Sagawa, K.; Nagatomi, R.; Inooka, H. Automatic classification of ambulatory movements and evaluation of energy consumptions utilizing accelerometers and a barometer. *Microsystem Technologies* **2005**, *11*, 1034–1040. doi:10.1007/s00542-005-0502-z.
113. Ichikari, R.; Ruiz, L.C.M.; Kourogi, M.; Kurata, T.; Kitagawa, T.; Yoshii, S. Indoor floor-level detection by collectively decomposing factors of atmospheric pressure. 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN). IEEE, 2015, pp. 1–11.
114. Li, Y.; Gao, Z.; He, Z.; Zhang, P.; Chen, R.; El-Sheimy, N. Multi-sensor multi-floor 3D localization with robust floor detection. *IEEE Access* **2018**, *6*, 76689–76699.
115. Atmospheric pressure. Available online: https://www.britannica.com/science/atmospheric-pressure, 2019. (accessed on 20/11/2019).
116. Cenedese, C.; Smith, P.J. Atmospheric pressure and wind. Available online: https://www.britannica.com/science/climate-meteorology/Atmospheric-pressure-and-wind, 2019. (accessed on 20/01/2020).

117. Le Blancq, F. Diurnal pressure variation: the atmospheric tide. *Weather* **2011**, *66*, 306–307. doi:10.1002/wea.857.
118. Giles, B. The atmospheric tide: an historical perspective. *Weather* **2012**, *67*, 51–53. doi:10.1002/wea.1895.
119. Trane. Commercial Building Pressurization. *TRANE engineers newsletter* **2002**, *31*.
120. Hendiger, J.; Chludzińska, M.; Ziętek, P. Influence of the pressure difference and door swing on heavy contaminants migration between rooms. *PloS one* **2016**, *11*, e0155159.
121. Lstiburek, J.; Pressnail, K.; Timusk, J. Air pressure and building envelopes. *Journal of Thermal Envelope and Building Science* **2002**, *26*, 53–91.
122. Zhang, N.; Zhou, D. Numerical Analysis of the Pressure Variation in Subway Tunnel When an On-Fire Train Runs at Different Speed; Advances in Civil,Environmental, and Material Research: Korea, 2016.
123. Reinke, P.; Flueckiger, M.; Wicht, T. Aerodynamics and ventilation in rail tunnels May 2015, 2015.
124. Barnes, J.D.; Brush, E.R.; Newmark, M.S.; Ungar, E.E. Dynamic Pressures on Tunnel Roofs due to Vehicle Passages. *SOUND & VIBRATION* **2018**, p. 6.
125. Orders of magnitude (pressure). Available online: https://en.wikipedia.org/wiki/Orders_of_magnitude_(pressure), 2019. (accessed on 20/01/2020).
126. Piston effect. Available online: https://en.wikipedia.org/wiki/Piston_effect, 2019. (accessed on 21/01/2020).
127. Why does atmospheric pressure change with altitude? Available online: https://www.npl.co.uk/resources/q-a/atmospheric-altitude-pressure-changes. (accessed on 20/01/2020).
128. Young, D.F.; Munson, B.R.; Okiishi, T.H.; Huebsch, W.W. *A brief introduction to fluid mechanics*; John Wiley & Sons, 2010.
129. De Montjoye, Y.A.; Hidalgo, C.A.; Verleysen, M.; Blondel, V.D. Unique in the Crowd: The privacy bounds of human mobility. *Scientific Reports* **2013**, *3*, 1–5. doi:10.1038/srep01376.
130. Zang, H.; Bolot, J. Anonymization of location data does not work: A large-scale measurement study. Proceedings of the 17th annual international conference on Mobile computing and networking, 2011, pp. 145–156.

© 2020 by the authors. Submitted to *Sensors* for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).