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Review

On the use of barometric sensors to track human activity

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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

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86 Displacement Activity (VDA), the accelerometer has been replaced by or at least given less importance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

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

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

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

117 2. General sensor data collection process to track human activities

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

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

132 *2.1. Sensors and sensor suites*

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

152 *2.2. Placement and orientation of the sensor*

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

163 *2.3. Sampling frequency*

164 The temporal resolution of the data is directly related to the sampling frequency of the sensor
165 used. For the vast majority of sensors used to carry out human activity recognition, the sampling
166 frequency typically ranges from 10 Hz to 100 Hz, with the rate going as high as 512 Hz. It is commonly
167 reported that the characteristic frequencies of most human activities are below 10 Hz, and therefore
168 the optimal sampling rate—based on the Shannon–Nyquist theorem—is 20 Hz [29]. Khan et al. [30]
169 reviewed 5 public datasets and showed that the sampling rate considered could be reduced between
170 48% and 86%, with a minimal sampling rate of approximately 12 Hz [30]. Yan et al. [31] also studied
171 the effect of sampling rate on energy consumption and they concluded that a higher sampling rate
172 increases energy load without providing additional meaningful information, in agreement with the
173 results reported in [30]. From the energy perspective, Yan et al. [31] concluded that a shorter dataset
174 with a higher sampling rate is preferable to a longer dataset at a lower sampling rate. It is worth
175 adding that the optimal sampling rate also depends on the type of human activity to be recognized [30]

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

180 2.4. Activity classes

181 Lara & Labrador [7] thoroughly reviewed a comprehensive list of human activities recognized and
182 categorized in the literature, including ambulation, transportation, gestures, exercises and daily living
183 activities. The activity classes may of course occur concomitantly and may therefore be composite [35],
184 interleaved, concurrent or overlapping [36]. For data with low sampling frequency, i.e. lower than
185 1 Hz, more than one activity could be performed during the same time interval. In particular, the class
186 of vertical displacement activities (VDA) has generally been recognized in the literature as part of the
187 larger class of ambulation activities. Similar to accelerometers, barometers are very well suited for
188 the recognition of VDA. In addition, barometers can accurately determine altitude changes for VDA
189 occurring at a sampling rate lower than 1 Hz.

190 2.5. Nature of data

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

207 2.6. Class imbalance

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

221 2.7. Diversity in physical characteristics

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

231 2.8. Annotation techniques

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

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

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

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

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

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

274 3.1. Barometric pressure sensor

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

283 3.2. Processing barometric sensor data

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

291 The time series data of barometric pressure is generally converted to statistical [70,92], spectral [70,
292 92], temporal [70,92] or wavelet-based features [75,93], before being fed into a classifier. These features
293 are designed to enhance the detection of the specific activity of interest. Most used features are based
294 on the rate of change of pressure [69,70,79,84,94] (also known as vertical velocity or simply the slope)
295 and the standard deviation of differential pressure (dp) [74,79], that differentiates altitude changes
296 from other environmental factors that influence ambient pressure.

297 3.3. Classifiers for sensed barometric pressure

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

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

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

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

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

327 3.4. Applications

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

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

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

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

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

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

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

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

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

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

399 Accelerometers are still the predominantly used sensors in HAR, and have been widely used as
400 stand-alone sensors in recognizing many activities of daily living. They complement barometer-based
401 recognition algorithm in detecting ambulatory movements such as walking, and their use helps also
402 distinguish stairs climbing from other modes of vertical transportation like elevator and escalator [69,
403 101]—and even elevator from escalator [67]. Sankaran et al. [79], however, point to the high cost
404 associated with the use of accelerometers: demands in data acquisition (position and orientation
405 dependent), high sampling rate, complex processing and classification training.

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

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

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

424 To summarize and categorize the vast breadth of applications of barometers for HAR, we have
 425 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 changes	altitude	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 changes	altitude	Altitude	Reduced position and orientation dependency using barometer	Ambulation	–	Short term
[95]	Barometer and Accelerometer	Estimate and changes	altitude and altitude	Altitude	Child activity recognition including VDA to prevent injuries	Ambulation	Indoor	Short term
[105]	Barometer and Accelerometer	Estimate changes	altitude	Altitude, climate & weather and sensor accuracy	Earliest known activity classification including VDA using barometer	Ambulation	Indoor	Short term
[97]	Barometer and Accelerometer	Estimate changes	altitude	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 changes	altitude	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 changes	altitude	Altitude, climate & weather, built environment and sensor accuracy	Improved recognition of VDA using barometer	Ambulation	Indoor	Short term
[67]	Barometer, Accelerometer, and Gyroscope	Estimate changes	altitude	Altitude	Improved identification of VDA for indoor localization	Ambulation	Indoor	Short term
[44]	Barometer and Accelerometer	Estimate changes	altitude	Altitude	Using barometer improved overall activity recognition including VDA and better estimate of energy expenditure	Ambulation	Indoor	Short term
[107]	Barometer	Estimate and changes	altitude and altitude	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 and changes	altitude and altitude	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 and changes	altitude and altitude	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 and changes	altitude and altitude	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 changes	altitude	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 and changes	altitude and altitude	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 change	altitude	Altitude	Activity recognition including VDA for better estimation of elderly physical activity	Ambulation	Indoor	Short term
[83]	Barometer and Accelerometer	Estimate changes	altitude	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 changes	door in building and altitude	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 and changes	altitude and altitude	Altitude	3D indoor localization	Ambulation	Indoor	Short term
[87]	Barometer	Detect patterns and estimate changes	gait and altitude	Altitude	Step detection and activity recognition including VDA using barometer	Ambulation	Indoor	Short term
[84]	Barometer	Estimate and changes	altitude	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 changes	altitude	Altitude	Determine location semantics such as restroom, desk, elevator, etc. using sensor fusion	Ambulation	Indoor and outdoor	Short term
[77]	Barometer and GPS	Detect patterns	vehicle	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 and changes	altitude and altitude	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 and changes	altitude and altitude	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 changes	altitude	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 patterns and altitude changes	vehicle and altitude	Altitude, climate & weather, built environment, and sensor accuracy	Identify transportation modes and ambulation activities using barometer	Ambulation and transportation	Indoor and Outdoor	Short term

[66]	Barometer	Estimate altitude and changes	altitude	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	Altitude	Identify the mode of vertical transport	Ambulation	Indoor	Short term

426

427 4. Factors affecting barometric pressure

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

431 Local atmospheric pressure is affected by several factors. From a fundamental point of view,
 432 these factors include the atmosphere's fluid properties such as density, moisture content, temperature,
 433 and motion. Speaking more generally, we can attribute the change in local barometric pressure to
 434 more abstract factors such as climate and weather [116–118], air velocity during motion, altitude, and
 435 built environment, with intricate interplays between all these factors. The magnitudes of the resultant
 436 effects vary and the corresponding ranges can be quantified for specific circumstances. Several studies
 437 have attempted to quantify these effects and provide a rich understanding of the factors that influence
 438 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]

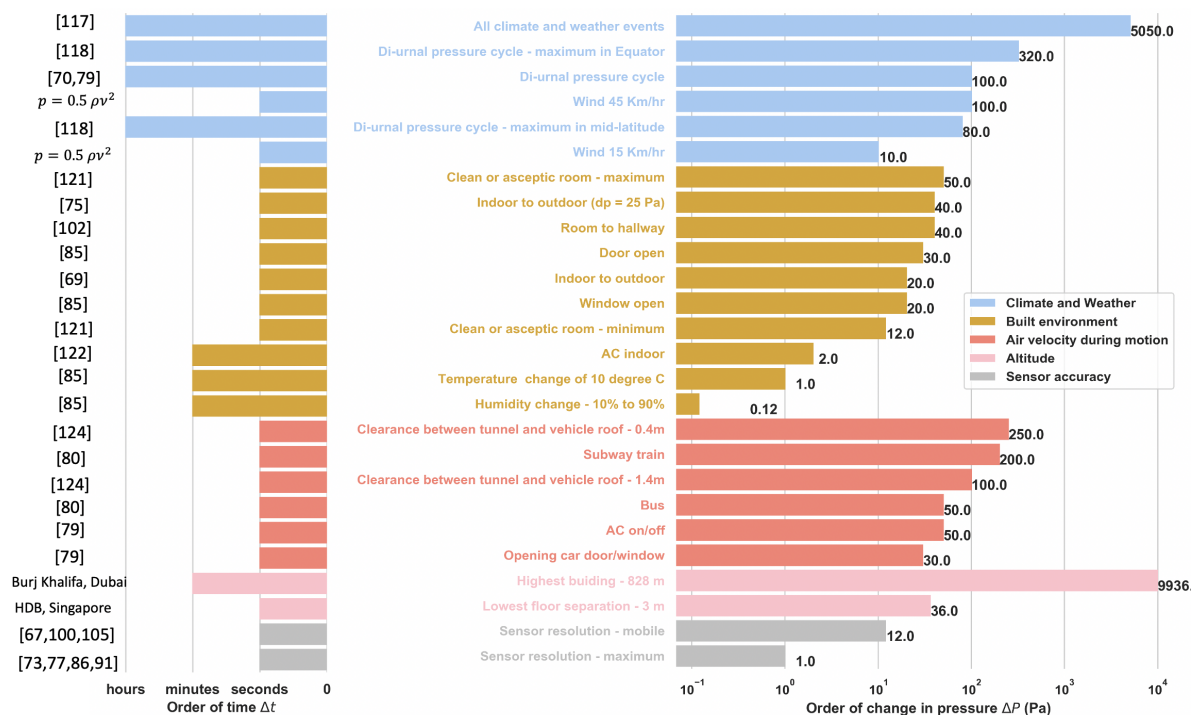


Figure 1. Orders of magnitude of changes in pressure and of the corresponding timescales for several factors influencing barometric pressure.

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 whatsoever. 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 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.

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

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

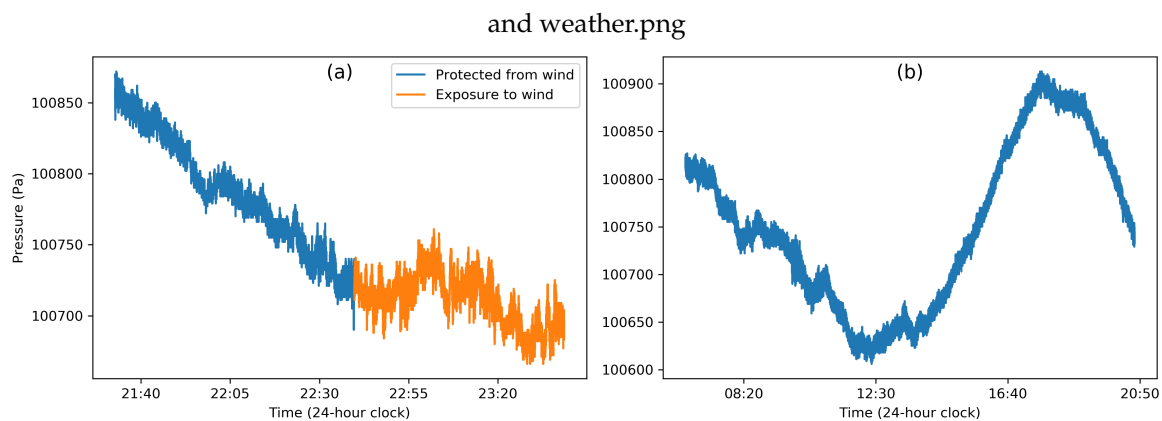


Figure 2. Climate and Weather (a) Diurnal pressure cycle in Singapore (b) Effect of wind. Recorded by custom-made device (barometer model - BMP280) with ~ 1 Hz sampling rate.

487 4.2. Built environment

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

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

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

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

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

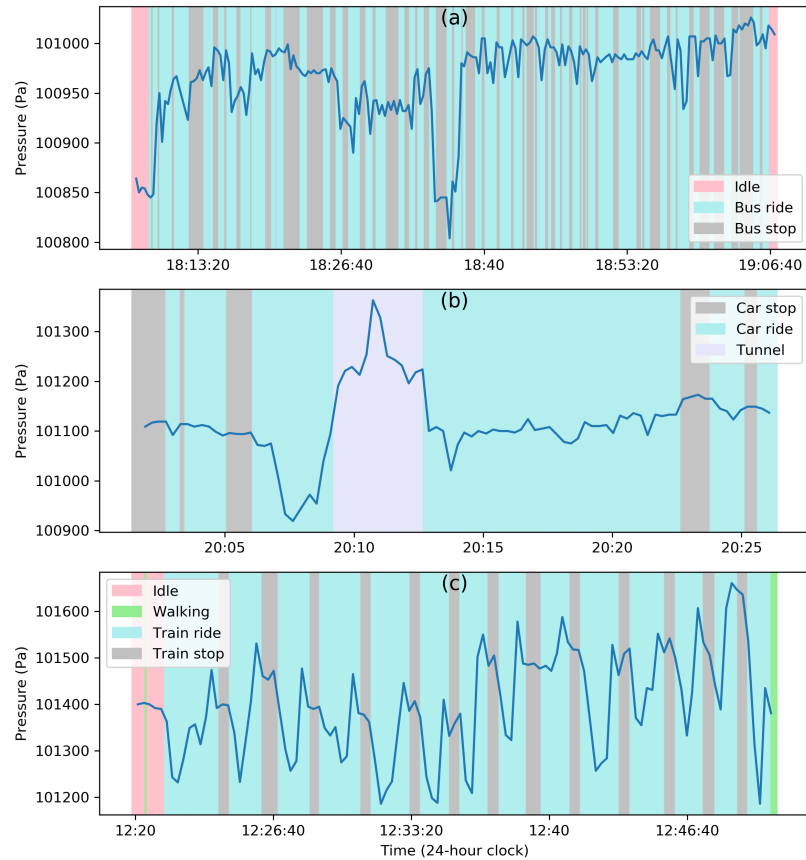
516 4.3. Air velocity during motion

517 Vehicles like cars and buses are in quasi-equilibrium with their environment due to the vents and
518 ducts allowing the airflow in. This means that the barometric pressure inside a vehicle is very close to
519 the exterior pressure. Note that the term 'exterior' denotes the air pressure in the immediate vicinity
520 of the vehicle and not the ambient pressure far from it, which could be drastically different. This is
521 due to the fact that ambient pressure is increased by the vehicle's motion near its surface where the
522 dynamic pressure increases and the static pressure falls. The stagnation pressure on the surface caused
523 by stopping the airflow near the surface produces a pressure distribution across the vehicle. This, in
524 turn, creates pressure fluctuations inside the vehicle whenever its motion changes. However, this effect
525 is transient and a quasi-equilibrium is reached quickly between interior and exterior. Figures 3a and
526 3b illustrate this behavior when a barometer is carried by a human subject during a bus and car ride
527 respectively, where limited pressure fluctuations (~ 50 Pa) are observed.

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

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

550 to 0.4 m. During subway rides, we can clearly distinguish between a train stop and motion [79] (see
 551 also Figure 3c). By combining this behavior with relative elevation data of train stations, Hyuga et
 552 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.

553 4.4. Altitude

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

561 them [127]. For all purposes involving human activity under 10 km altitude above sea-level, it is safe
 562 to assume a linear relationship with altitude that typically shows a pressure decrease of 115 Pa per 10
 563 meters climb [115]. As an illustration of the magnitude of the effect in the context of human activities,
 564 Figure 4 shows the barometric pressure change due to change in elevation through different vertical
 565 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

$$z_2 - z_1 = -\frac{p_2 - p_1}{\gamma}, \quad (1)$$

566 where $\gamma = \rho g$ is the specific weight of air with density $\rho = 1.225 \text{ kg/m}^3$ and acceleration due to gravity
 567 $g = 9.81 \text{ m/s}^2$ at standard sea-level conditions. This pressure-altitude elevation holds with negligible
 568 errors as long as the elevation under study is less than 10 km from sea-level [128], which is the case in
 569 most studies.

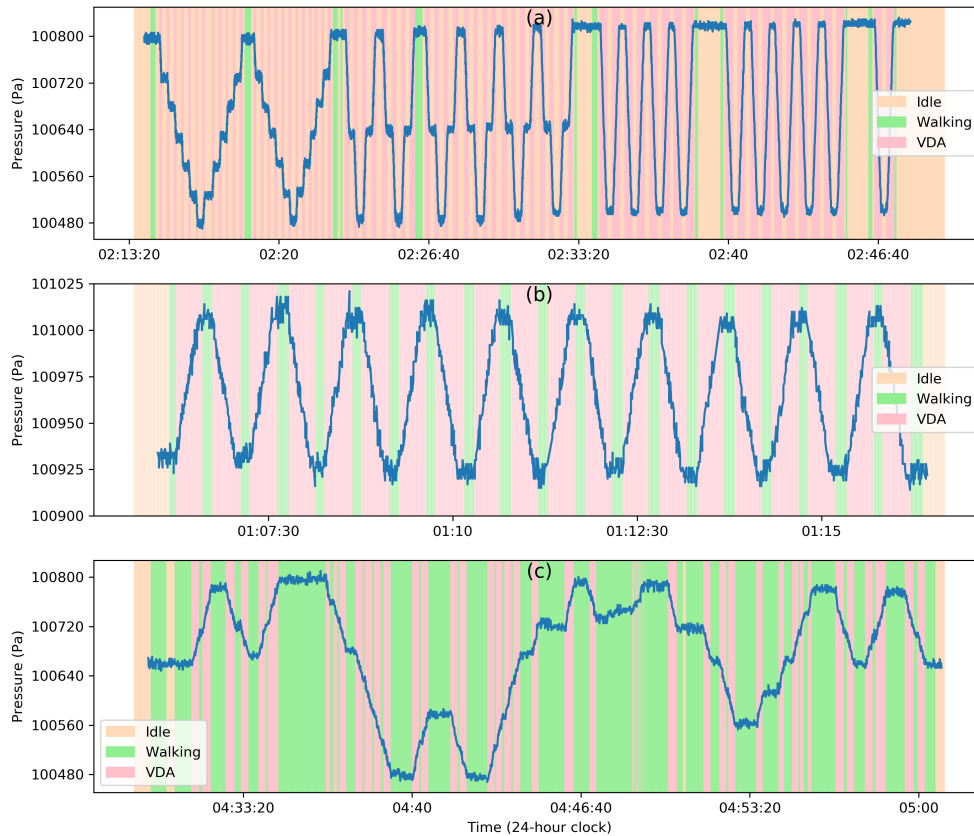


Figure 4. Effect of variations of altitude during human activity and motion. (a) Elevator (b) Escalator (c) Stairs. Data was collected by carrying a mobile device with a sampling rate ~ 1 Hz on different modes of vertical mobility. For panel (a), the elevator was intentionally stopped at each floor in 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 ± 1 meter.

570 4.5. Sensor accuracy

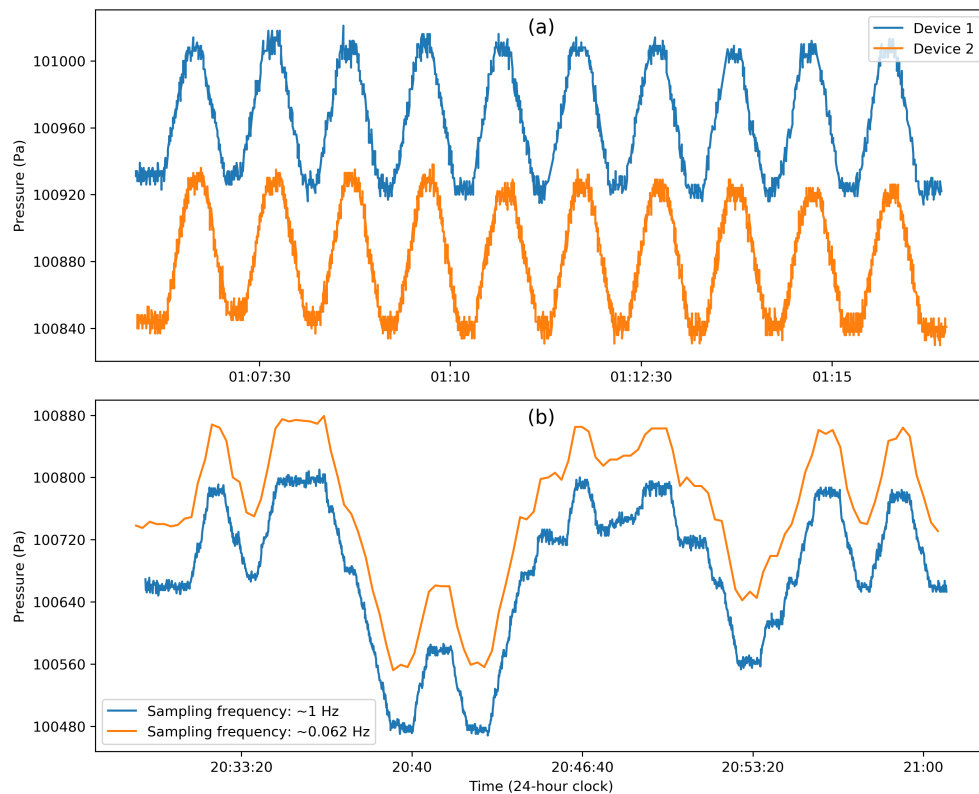
571 The quality of measurement of barometric pressure is limited by the sensor's accuracy. Both
572 absolute and relative barometric pressure can change between devices due to differences in sensors
573 and their characteristics. Here, the ensuing measurement errors are defined as caused by such inherent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

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

587 *Sensor resolution:* The accuracy of the barometer is dependent on the built-in resolution of the
588 sensor. Barometers embedded in mobile devices have generally a relative accuracy of ± 10 Pa [66,99,
589 104], while commercially available high-resolution sensors can reach an accuracy of ± 1 Pa [72,76,85,90].
590 Sensor resolution is also affected by the measurement errors caused by noise. Haque et al. [72] used
591 Allan Deviation (ADEV), a time domain analysis, to estimate the non-stationary errors of four different
592 barometer models and listed the random noise processes that are dominant for a given observation
593 period.

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

598 *Sampling frequency:* the recording frequency determines the completeness of the data. Weather
599 stations generally send out data every hour, while mobile barometers embedded in mobile devices
600 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].
601 Depending on the activity to be recognized, this sampling frequency should be set appropriately to
602 capture the actual time scale of the activity. As an illustration, Figure 5-b shows the time series of
603 barometric pressure recorded by two devices with different sampling rates - 1 Hz and 0.06 Hz. It
604 shows that altitude might not be accurately estimated during certain periods if the sampling rate is not
605 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 ~ 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, ~ 1 Hz and ~ 0.062 Hz respectively. This panel shows how the sampling rate affects the detection of altitude changes.

606 5. Future research

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

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

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

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

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

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653 **Abbreviations**

654 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
655 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

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