Towards Human Posture Detection Based on Differential Measurements Using Wearable Barometric Pressure Sensors

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Abstract: The detection of human postures is a well-studied research area that is closely related to human activity recognition. Recent advantages of MEMS-based barometric pressure sensors have made them an interesting additional sensing modality apart from IMU-based approaches. State-of-the-art barometric pressure sensors allow for measuring changes in barometric pressure corresponding to height differences in the range of centimeters. However, they are susceptible to environmental pressure changes, which can significantly influence the application. Therefore, we propose a posture detection approach based on differential height measurements from multiple body-worn barometric pressure sensors. We conducted an initial laboratory study with 13 subjects (eight males and four females), evaluating standing, sitting, and lying down postures using four body-worn barometric pressure sensors positioned at the head, hip, wrist, and ankle. Our results demonstrate that only two sensors are needed to separate the studied postures in the feature space. Furthermore, the differential height measurement approach can compensate for environmental pressure influences to an insignificant level w.r.t. posture separability in our setup. The efficacy of our proposed approach is further substantiated by the observed separability of sitting on a bed and a chair for each subject individually.

1 INTRODUCTION

Barometric pressure sensors have found their way into Human Activity Recognition (HAR) systems since the 1990s (Manivannan et al., 2020). Due to their ability to capture atmospheric pressure, which decreases with increasing altitude, they deliver valuable information on the altitude of a person when attached or worn, e.g., in a smartwatch (Afram et al., 2022). State-of-the-art Micro-Electro-Mechanical Systems (MEMS) barometric pressure sensors, such as the BMP581 from Bosch Sensortec (Bosch Sensortec GmbH, 2024), can measure pressure changes corresponding to height differences of a few centimeters and are nowadays ubiquitous in devices like smartphones or smartwatches. This makes them a valuable option for enhancing HAR and smart health monitoring systems in terms of detection accuracy. In contrast to standard inertial measurement unit (IMU)-based approaches, which are only able to detect relative movements or absolute orientations, barometric pressure sensors are able to provide absolute height information along the gravitational axis.

The present paper proposes human posture detection based on height differences between body parts obtained from multiple body-worn barometric pressure sensor measurements. This can be seen as a first step towards the aforementioned improvement of HAR systems, which we suspect will be especially useful for distinguishing activities that share a similar movement profile within IMU data but are performed with different body postures.

Our paper is structured as follows: Section 2 explains related literature and how our contribution differs. Section 3 describes our proposed concept. Our feasibility study is described in section 4 followed by the evaluation of the acquired results in section 5. Finally, we discuss our findings in section 6 and present conclusions in section 7.

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2 RELATED WORK

The related literature to our approach can be categorized into three topics: general human posture detection approaches, IMU-based HAR and health monitoring approaches including barometric pressure sensors, and applications based only on barometric pressure sensors. In the following, the related literature will be discussed in that order.

The predominant posture detection approach in the literature is based on camera recordings. Many different posture detection applications exist in this field, such as human fall detection (Sun and Wang, 2020) or posture estimation for sports activities (Nadeem et al., 2021). For a detailed overview, readers are referred to the survey (Ma et al., 2022).

However, camera-based systems are usually more expensive and require complex camera alignment and optical markers, which can be hidden during postures or behind objects. This limits camera-based approaches to laboratory conditions making wearable sensor-based posture detection an interesting alternative, which is practically not limited to stationary setups.

While some existing approaches incorporate only accelerometers to detect the tiltation of the human body for posture estimation (Chopra et al., 2016) or to infer the posture by multiple accelerometers (Wang et al., 2016b), others combine them with additional sensor modalities, e.g., electromyography sensors attached to the upper limb in combination with accelerometers to infer the upper body posture (Li et al., 2021). Similar to our proposed approach, some other studies suggest to infer body postures by distance measures between wearable sensors. In (Vecchio et al., 2017), ultra-wideband trackers have been used to calculate distances, and in (Matsumoto and Takano, 2016), the Received Signal Strength Indicator (RSSI) of Bluetooth Low Energy (BLE) beacons have been used. The survey on wearable sensor-based human motion and posture monitoring in (Huang et al., 2023) shows that barometric pressure sensors play no significant role in existing posture detection approaches.

However, barometric pressure sensors have already been widely investigated for tracking human activities. The work of Manivannan et al. (Manivannan et al., 2020) provides a good overview of the research topics and challenges regarding the usage of barometric pressure sensors for HAR. Many approaches presented in the literature fuse sensor data of barometric sensors with other sensing modalities like IMUs.

Most common approaches make use of additional barometric pressure sensors in order to detect if a person is inside or outside of a building and its transitions (Zhu et al., 2020) or different modes of vertical transportation, e.g., riding an elevator (Liu et al., 2018), climbing up and down (Nam and Park, 2013; Xu and Qiu, 2021; Leuenberger et al., 2014), or floor localization (Xu et al., 2017; Liu et al., 2014). This also includes studies on vertical velocity and height information (Sabatini and Genovese, 2014). The same idea was also applied to activities that involve the vertical displacements of the entire body, i.e., falling detection (Bianchi et al., 2010; Wang et al., 2016a; Ejupi et al., 2017b; Pierleoni et al., 2016).

In (Ejupi et al., 2017a), (Massé et al., 2016), (Xie et al., 2018), and (Massé et al., 2015), a single barometric pressure sensor in combination with IMU sensors was used to classify sit-to-stand and stand-to-sit transitions. While this can be categorized as a posture change detection, the single sensor approach lacks a reference and might lead to misclassifications, especially when sitting or lying surfaces are at different heights or environmental disturbances through, for example, opening or closing doors or windows are present. In contrast, our approach uses multiple barometric sensors for differential pressure evaluation. This leads to the detection of relative height differences, which helps to distinguish postures independent of the altitude at which the postures are adopted and allows the removal of disturbances common to all pressure sensors. This compensation approach has already been suggested in (Audisio, 2024) for tracking the body's center of mass during human activities, although it has not been implemented and tested yet.

Other studies that involve multiple barometric pressure sensors for HAR classification are (Makma et al., 2021) and (Moncada-Torres et al., 2014). While in (Makma et al., 2021), the difference of a single body-worn barometric pressure sensor to a stationary wall-mounted reference sensor is utilized, (Moncada-Torres et al., 2014) used the altitude changes relative to the individual arithmetic mean of multiple body-worn barometric pressure sensors. In contrast, our approach utilizes the relative differences between all body-worn barometric pressure sensors to cancel out environmental influences affecting all sensors and infer the adopted body posture.

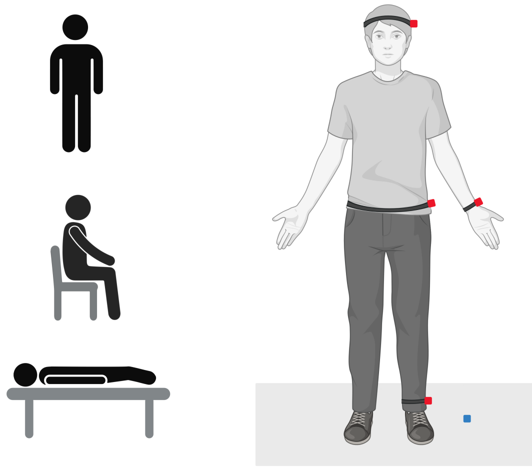
Finally, examples of applications that use barometric pressure sensors only include altimetry measurement systems (Bolanakis, 2017b; Bolanakis, 2017a) and the detection of opening and closing events of doors inside a building (Wu et al., 2015). Furthermore, in (Bollmeyer et al., 2013) and (Bollmeyer et al., 2014), altitude information of a person in medical applications is calculated based on differential measurements. Again, only one body-worn sensor is used together with a stationary reference measurement. In (Vanini et al., 2016), the barometric pressure sensor of a smartphone is used to distinguish between standing/walking on level ground and climbing stairs, riding an elevator, and riding a cable car. Ghimire et al. (Ghimire et al., 2016) studied the classification of motion states (resting, walking, riding an elevator) using a single body-worn barometric pressure sensor. Similarly, in (Massé et al., 2014), a single trunk-worn barometric pressure sensor is used to distinguish standing and sitting activities. The most similar approach regarding the measurement of differential pressure between multiple body-worn barometric pressure sensors was proposed by Sun et al. in (Sun et al., 2019). They used two body-worn barometric pressure sensors to detect a person's falling in different scenarios by calculating the height information of a waist-worn sensor to a reference sensor attached to the shoes. Although they state that the reference sensor can be mounted stationary or removed completely, the detection accuracy may drop. This substantiates the potential of our proposed approach to differential barometric pressure measurements for detecting human postures, which can be seen as an extension of the aforementioned approaches towards detecting human postures.

3 CONCEPT

As described earlier, our approach is based on multiple barometric pressure sensors attached to different body parts, which gives us the following advantages:

Differential Height Measurements: between the sensors can be extracted from the minor relative changes in barometric pressure due to different postures. Recent MEMS-based sensors enable us to measure pressure changes corresponding to a few centimeters, which lies in the range needed to detect height differences between body parts.

Compensation of Environmental Influences: will be enabled due to the correlation of disturbances in all accelerometers. Besides useful information regarding the pressure on different body parts, the data also contains disturbances induced by events in the environment of the measurement setup. These could be caused by opening or closing doors or windows in the building or by barometric pressure changes due to weather conditions like wind. We suspect that these events influence the barometric pressure measurements of all sensors similarly, enabling the elimination by considering only the height differences.



(a) (b)

Figure 1: (a) Examined body postures standing, sitting, and lying (b) Visualization of the placement of the four body-worn sensors (red) at the head, wrist, hip, and ankle as well as the reference sensor placed on the ground (blue). The reference sensor is not involved in the posture detection but is used to evaluate environmental influences in barometric pressure. (Created in BioRender. Geiger, F. (2024) https://BioRender.com/f38h800).

Table 1: Execution sequence of the user study.

1. Standing	6. Sitting on a bed
2. Sitting on a chair	7. Lying down on a bed
3. Standing	8. Sitting on a bed
4. Lying down on a bed	9. Standing
5. Standing	

4 EXPERIMENTS

4.1 User Study

The aim of the experiment is to assess how well a person's posture can be inferred from multiple body-worn barometric pressure sensors. To this end, our study was conducted under laboratory conditions, minimizing additional environmental influences as much as possible. Therefore, the experiments were conducted in a computer lab on the second floor of a 4-floor building with an approximate area of 85 m^2 and a ceiling height of 3.30 m. The doors and windows were kept closed during the experiments, and the air conditioning was turned off to minimize environmental influences on the barometric pressure. The experiments were conducted from 10 am to 4 pm, and the room temperature varied between 21.1 °C and 21.5 °C during the experiment.

The study involved 13 healthy subjects (eight males and five females) with an average age of

34.6±9.6 years. Ethical approval was granted by the Ethics Committee of the Rostock University Medical Center, Germany (A 2024-0138). The average body height was 181±13 cm, with the tallest subject measuring 208 cm and the shortest subject measuring 161 cm. The subjects were instructed to follow a predefined sequence of nine postures specified in Table 1, which involved standing, sitting on a chair, sitting on a bed, and lying on a bed. In our setup, a field cot served as the bed. The postures are displayed in Figure 1a. In order to capture execution variations of the same subject, the sequence was repeated three times per subject, and each posture was held for approximately 10 s. In the first trial, no specific instructions were given on how to sit, stand, or lay down. For the second and the third trial, the following instructions were given to the subject:

- standing straight with hands hanging down beside the body
- sitting straight with hands on the knees
- lying flat on the bed with the hands resting beside the body

The chair and the field cot were placed close to each other to minimize transition times. Measured from the floor, the height of the chair was 48 cm, and the height of the field cot was approximately 40 cm.

4.2 Hardware Setup

The hardware setup for our study consisted of four wearable sensor nodes attached to the human body and a single sensor node on a fixed location on the floor within a perimeter of 2 m from the subject. The latter was implemented to analyze environmental influences on the barometric pressure data unaffected by the subject's movement. Note that the pressure data from the reference sensor is not required or used for our posture detection, which permits mobile applications. As can be seen in Figure 1b, the sensors were attached to the head, hip, wrist, and ankle using hook-and-loop fasteners. Each sensor node consists of a BMP581 barometric pressure sensor from Bosch Sensortec GmbH, Reutlingen, Germany. The sensor nodes attached to the hip and the head, as well as the reference sensor on the floor (in the following referred to as hub nodes), were additionally equipped with a microcontroller board based on an nRF52832 microcontroller with integrated BLE chip from Nordic Semiconductors. The sensor nodes at the ankle and wrist were wired to the hub nodes at the hip and the head, respectively. The hub nodes sampled the barometric pressure sensors via I²C at a rate of 12 Hz and sent the data wirelessly to a laptop via BLE. Each barometric pressure sample was transmitted in an individual BLE packet. The Unix timestamp on the laptop at the arrival of each BLE packet was used as the timestamp for each pressure sample.

To annotate the data with corresponding ground truth labels, we marked the recorded postures by implementing two recording states, switched via a button press. The state (*posture* or *transition*) was recorded together with the barometric pressure data and their timestamps and was used to distinguish between posture and transitions. Together with the known execution sequence of postures, all posture states were annotated with their corresponding label in post-processing. It is important to note that the instructor first switched the recording state from posture to transition before instructing the subject to change to the next posture in the sequence and switched back to the posture recording state after the subject took its instructed position. This way, no transitions are contained in the posture-labeled data.

4.3 Data Processing

Due to manufacturing tolerances, there are variations in barometric pressure measurements between different sensors, even when placed at the exact altitudes. To compensate for these variations, we calibrated the sensor nodes before each recording of a subject. Afterwards, the data was resampled by linear interpolation, and the height differences were calculated.

4.3.1 Calibration

Before each subject's trial, all sensor nodes were placed on the ground, and a short sequence of pressure values was collected. The mean pressure values over the recording were calculated for each sensor, and the absolute differences to the ankle sensor were calculated. This absolute difference was then subtracted from the measured pressure sequences in all other sensors to compensate for absolute pressure offsets. This calibration between the sensors attached to the body allows for posture detection independent of any stationary sensors.

4.3.2 Height Differences

In order to calculate height differences between the sensor nodes, first their absolute altitude w.r.t. sea level has been calculated by the barometric formula using equation (1), with subscript b denoting values for the lowest atmospheric layer from 0-11,000 m above sea level, P_b being the static pressure at sea level (here: $P_b = 1{,}013.25$ hPA), T_b being the standard temperature at sea level (here: $T_b = 288.15$ K),

L_b being the standard temperature lapse rate (here: $L_b = 0.0065 \frac{K}{m}$), h_b being the height at the bottom of atmospheric layer (here: $h_b = 0$ m), R the universal gas constant ($R = 8.3145 \frac{J}{mol \cdot K}$), g_0 gravitational acceleration ($g_0 = 9.80665 \frac{m}{s^2}$), and M molar mass of air ($M = 0.0289644 \frac{kg}{mol}$).

$$h = h_b + \frac{T_b}{L_b} \cdot \left[1 - \left(\frac{P}{P_b} \right)^{\frac{-R \cdot L_b}{g_0 \cdot M}} \right] \tag{1}$$

From the absolute altitude values, height differences between the individual sensor nodes have been calculated.

Since no additional synchronization between sensor hub nodes was implemented, barometric pressure data was sampled equidistantly but not necessarily at the exact same time between different sensor hub nodes. To calculate height differences at specific timestamps, the absolute height measurements from all sensors were resampled at a common time base using linear interpolation between samples.

5 EVALUATION

The raw pressure values were calibrated to the ankle sensor as described in section 4.3.1 and are displayed in Figure 2 for trial 1 of subject 2. The sections highlighted in green mark the transition phases when the subject changes between the postures. Each colored line denotes one of the pressure sensor readings, and the transparent numbers denote the execution order according to Table 1. Note that the reference sensor (purple) is only included for the visual analysis of environmental pressure fluctuations. As this sensor is stationary on the floor, the measured pressure is expected to be constant during the trial. However, throughout the trial, the graph shows larger bumps from approximately 5-25 s, 45-55 s, and 110-135 s. We assume this is caused by events in the building that were outside of our control, e.g., opening/closing doors or windows in other rooms or corridors. The pressure changes due to posture changes, e.g., between phases 5, 6, and 7 (standing, sitting, and lying down), are in the same order of magnitude, further substantiating our motivation for using height differences between sensors for the classification. While the observed disturbances significantly influence the absolute pressure, the relative pressure differences between the sensors remain nearly the same.

Figure 3 is similar to Figure 2 except that each colored line now represents the height differences between the sensors attached to subject 2 during trial 1. It can be seen that the calculation of height differences compensates external influences in barometric pressure to the greatest extent (cf. Figure 2). This shows that the external variations influence all attached sensors similarly. Overall, minor fluctuations remain visible in all graphs, likely caused by the noise of the sensors and insufficient sensor synchronization. Nevertheless, these fluctuations are significantly smaller than the differences in height caused by different postures.

Similarly to Figure 2, the postures can be visually inferred from the graphs. As expected, the height differences between head and ankle, wrist and ankle, and hip and ankle decrease when transitioning from standing (phases 1, 3, and 5) to sitting (phases 2, 6, and 8) and to lying down (phases 4 and 7). The height difference between head and hip and between head and wrist remains nearly the same between standing and sitting but decreases when lying down. In contrast, the height difference between hip and wrist does not substantially change between the postures. Interestingly, minor differences are visible between phases 2 and 6, where the subject sat on the chair and the bed, respectively. As the bed's surface was lower than the chair's surface, the height difference between hip and ankle and between head and ankle are less for sitting on the bed (phases 6 and 8).

To select the most suitable sensors for posture detection, the distributions of the height differences between all body-worn sensors are depicted as histograms in Figure 4. The x-axis marks the distance calculated for the corresponding sensor combination, the y-axis shows the number of occurrences in our dataset, and the color denotes the corresponding postures: standing (blue), sitting (orange and green), and lying down (red). Looking at the distribution of the height difference between wrist and hip, a straightforward separation of the postures is impossible, as the distributions for the different postures significantly overlap. In contrast, the distributions of the height differences between head and ankle and between hip and ankle show a clear separation between the postures. This could allow for a simple classification using a threshold even without normalizing the sensor height differences to the corresponding body height. Similar to before, when looking at the difference in height between head and ankle and between hip and ankle, minor differences are visible between distributions for sitting on the chair and sitting on the bed, although they have a significant overlap. The difference between the distributions becomes even more evident when looking at the subjects individually. This is an interesting result as the height difference between the chair and the bed was only 8 cm. However, we suspect that discrimination in non-laboratory conditions,

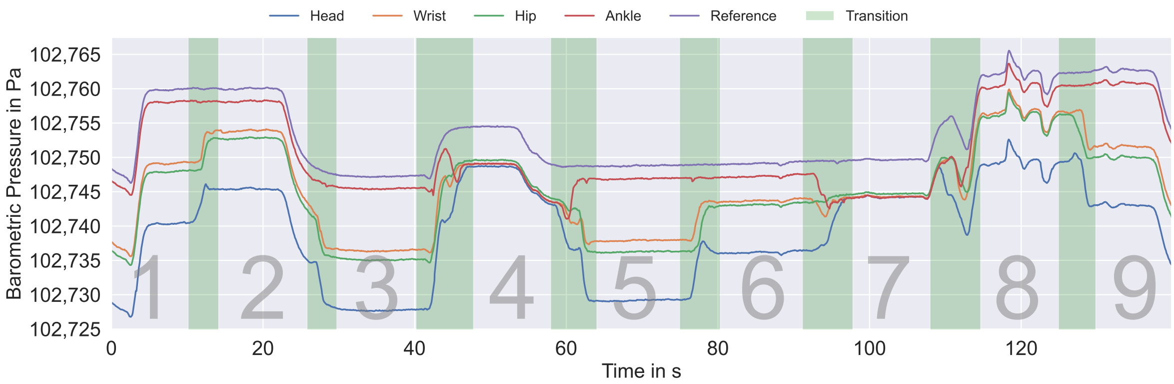


Figure 2: Pressure values calibrated to the ankle sensor for subject 2 in trial 1.

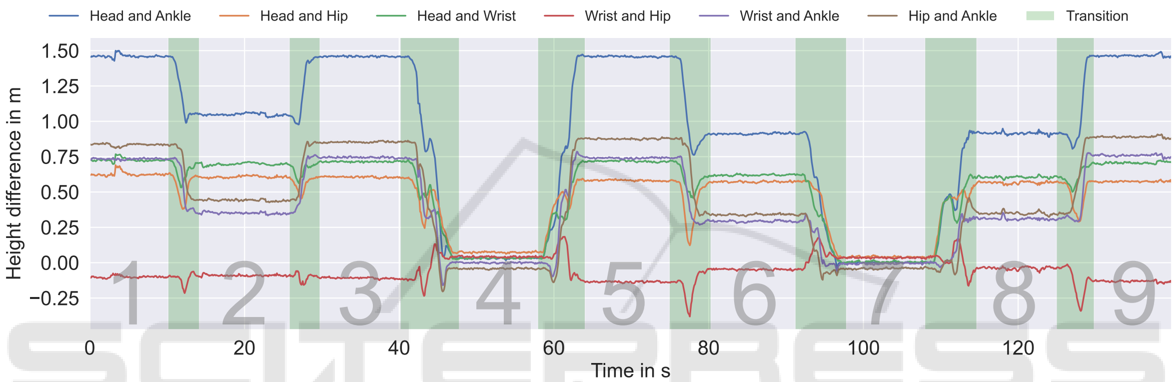


Figure 3: Height differences between the sensors calculated for subject 2 in trial 1.

Table 2: Values of $\frac{S_B}{S_W}$ for each possible combination of sensors.

Sensor Combination	$\frac{S_B}{S_W}$
Head and Ankle	$2,247 \cdot 10^3$
Head and Hip	$386 \cdot 10^3$
Head and Wrist	$478 \cdot 10^3$
Wrist and Hip	$20 \cdot 10^3$
Wrist and Ankle	$487 \cdot 10^3$
Hip and Ankle	$495 \cdot 10^3$

where the subjects might sit differently (e.g., straight vs. laid back), will be more difficult.

To determine a quantitative measure of posture distinguishability, we utilized a metric that quantifies the separability of data distributions, which is adopted from multiclass linear discriminant analysis (Tharwat et al., 2017). To this end, each posture (standing, sitting, lying down) is considered a class. The variance between the classes S_B and the variance within the classes S_W are calculated, and their ratio, which is subject to maximization in linear discriminant analysis, is used as a measure of separability. We calculated S_B and S_W for the one-dimensional height differences with the following equations, where X is the set of samples $x \in X$, C is the set of classes $c \in C$, n_c is the number of samples belonging to c, N is the total number of samples $N = \sum_{c \in C} n_c$, μ_c is the class mean of all samples belonging to c with

$$\mu_c = \frac{1}{n_c} \sum_{j \in c} x_j \,,$$

and μ is the mean of all samples

$$\mu = \frac{1}{N} \sum_{x \in X} x \,.$$

$$S_B = \sum_{c \in C} n_c (\mu_c - \mu)^2 \tag{2}$$

$$S_W = \sum_{c \in C} \sum_{j \in c} (x_j - \mu_c)^2 \tag{3}$$

We used $\frac{S_B}{S_W}$ as a measure of separability between the posture classes for each sensor combination. Note that the measured height differences per subject were normalized for the calculation by the overall height of the corresponding subject to compensate for different subject heights. The calculated values for all sensor combinations are shown in Table 2.

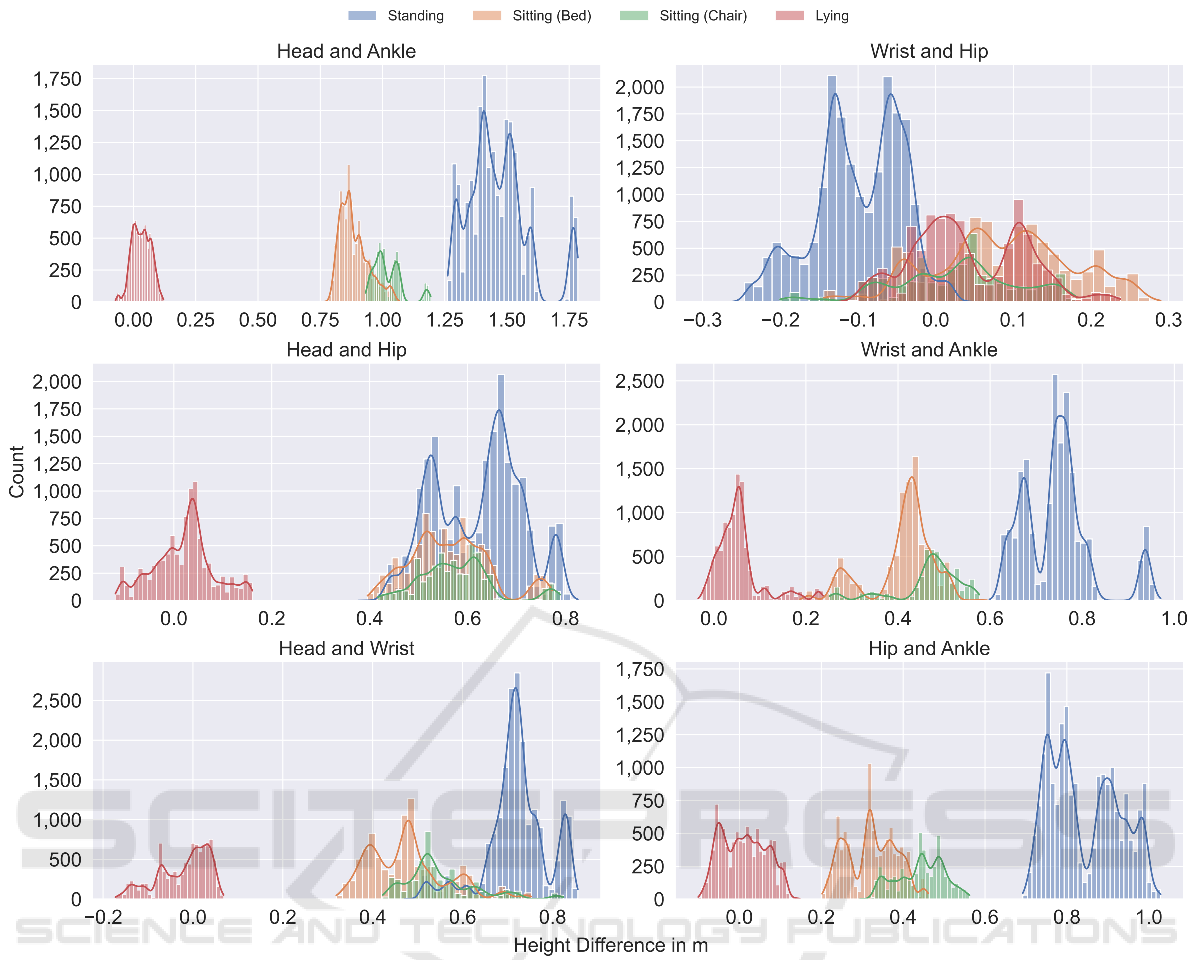


Figure 4: Distribution of postures over all height differences between the sensors.

As expected, the highest value is obtained for the height difference between the head and the ankle. The second highest value is obtained for the height difference between hip and ankle, although the height difference between wrist and ankle and between head and wrist have similar values. The lowest value was obtained for the height difference between the wrist and the hip, which aligns with our initial visual analysis. This supports our previous assumption that the height differences between head and ankle and between hip and ankle are best suited for separating the postures.

Figure 5 displays the distributions for each posture along the height difference between head and ankle (x-axis) and between hip and ankle (y-axis) in a two-dimensional feature space. Both differences were scaled per subject according to their body height, which causes slightly more compact distributions. Consistently with the previous results, the posture classes standing (blue), sitting (orange and green), and lying (red) are clearly separated in the feature space, which suggests a simple classification using predefined thresholds or simple algorithms like decision trees or a k-nearest-neighbor. Looking at the separability of sitting on a chair and sitting on a bed, we can see differences in the centroids of the two-dimensional distributions. Nevertheless, there is a significant overlap between the two distributions, which would lead to a certain amount of misclassifications. Similar to previous analyses, the examination of the graphs for individual subjects indicates better separation of the distributions between sitting on the chair and the bed. Although we have scaled the height differences with the body height, the overlaps could be caused by variations due to the sensor placement on the subjects and the movement of the sensor during the experiments.

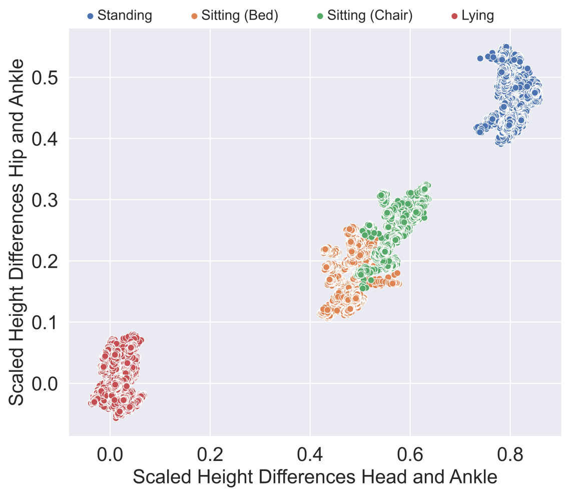


Figure 5: Distribution of the postures over the height differences between head and ankle as well as hip and ankle.

6 DISCUSSION

Our work presents a feasibility study targeting human posture detection using barometric pressure sensors. The novelty lies in using the differential altitudes between multiple barometric pressure sensors, which are all directly attached to the subject. However, our feasibility study has several limitations which require further investigation.

Firstly, only three distinct static postures were evaluated. Deciding between more similar postures will be more challenging, but our analysis showed differences between sitting on the bed and the chair, indicating the significant potential of our approach.

Secondly, our differential approach showed robustness against the air pressure disturbances present in our laboratory data, consistent with earlier studies on barometer-based indoor floor localization (Liu et al., 2014) and indoor altitude estimation (Bollmeyer et al., 2014). Nevertheless, the effects of more severe environmental disturbances of the air pressure, as expected in real-world scenarios, require further investigation.

Another limitation of our study is the uncompensated pressure drift of the barometric pressure sensors and the simplistic time synchronization between the sensors. While the recordings were relatively short in our experiments, the effects mentioned above might lead to inaccuracies during long-term monitoring, which needs additional compensation. Moreover, our feasibility study excluded the classification of transitions between postures, which would require more sophisticated algorithms and introduce additional challenges, e.g., due to overlaps in the transitions. Also, the selected postures were limited in their execution variation, and postures during activities, e.g., upright posture in activities like walking or running, were not considered. This could introduce additional disturbances, such as local barometric pressure changes, due to air compression in front of a person. The influence on the local barometric pressure is currently unknown to us. Still, we suspect that the differential height approach might also help to compensate for this effect under the assumption that all sensor nodes are equally affected by this.

The abovementioned limitations highlight that our work presents the first results towards a robust posture detection approach using the height differences measured with multiple body-worn barometric pressure sensors. However, the observed separability between the examined postures and the observed compensatory ability of differential measurements in our experiments motivate further research in this direction. Furthermore, contrary to standard IMU sensors, which are only able to detect relative movements or absolute orientations, our approach is able to deliver an absolute height difference along the gravitational axis.

7 CONCLUSION

In the paper at hand, we propose a posture detection approach based on differential height measurements from wearable barometric pressure sensors. We evaluated our approach in an initial user study with 13 subjects under laboratory conditions, examining the postures of standing, sitting, and lying down on a bed with barometric pressure sensors attached to the head, hip, wrist, and ankle of each subject. Our evaluation showed that a combination of two sensors is sufficient to discriminate all examined postures in our experiment. Furthermore, the proposed differential height measurement approach successfully compensated for environmental influences on the barometric pressure sufficiently in our study. The separability of each subject's sitting posture at different surface heights further substantiates our proposed posture detection approach. In future work, we will concentrate on enhancing the robustness of our approach w.r.t. environmental influences in real-life scenarios, as well as its potential application to health monitoring applications, e.g., the estimation of joint angles. Furthermore, the improvement in distinguishability of activities in HAR systems by accurate posture detection using barometric pressure sensors remains to be evaluated.

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INSTITUTIONAL REVIEW BOARD STATEMENT

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the Medical Faculty, University of Rostock (registration number A 2024-0138).

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