Abstract—We present a new scheme to automatically identify the locations of wearable sensor nodes in a wireless body area network (WBAN). Instantaneous atmospheric air pressure readings are compared to map nodes in physical space. This enhancement enables unassisted sensor node placement, providing a practical solution to obtain and continuously monitor node locations without anchor nodes or beacons. To validate this localization scheme, a statistical analysis is conducted on a set of air pressure sensors and a prototype WBAN to examine the performance and limitations. Based on a 60 cm separation between nodes, indicative of the expected separation between limbs and placement positions along a patient’s body, the measurements consistently exceeded \( p \)-value reliability within a 95% confidence interval. We also present and experimentally demonstrate an enhancement aiming to reduce false-positive (Type I) errors in conventional accelerometer-based on-body fall detection schemes. Our statistical analysis has shown that by continuously monitoring the patient’s limb positions, the WBAN would be better able to discriminate “fall-like” motions from actual falls.

Index Terms—Atmospheric air pressure, fall detection, health monitoring, limb tracking, m-health, node identification, sensor placement, wearable sensors, wireless body area network (WBAN).

I. INTRODUCTION

WIRELESS body area networks (WBANs) are increasingly becoming plausible solutions for on-body health monitoring and diverse medical applications. This can be largely attributed to the decreasing physical size and production costs of microelectromechanical systems (MEMS) sensor technology. Existing health monitoring devices fulfill the aim of being apt for long-term use. However, there is a widespread consensus that replacing wired devices with wearable wireless sensor nodes (WWSNs), designed to measure the vital signs of the patient’s body, is more desirable due to the inherent freedom of movement that the wearer gains. These externally worn nodes often take the form of armbands, leg straps, and adhesive pads to allow for easy removal prior to activities such as showering and swimming, where the nodes may otherwise interfere or malfunction. Unfortunately, this added flexibility increases the chance of misplacing WWSNs after a certain activity is finished and they need to be worn again. A patient could muddle up the nodes, causing, for example, the arm node to record leg motion, and vice versa. Depending on the nature of the long-term monitoring and the frequency at which data are analyzed by the clinician or caregiver, node misplacement could yield conflicting data with the expected patterns at the intended node location. For example, a clinician analyzing arm and leg tremors for dyskinesia symptoms in Parkinson’s disease patients may collect inconsistent data if the sensors’ physical placements over the patient’s limbs mismatch their correct target locations.

Currently, WWSNs are typically manually programmed for collecting data consistent with certain locations of a patient’s body, such as an arm or leg. Sensor nodes have limited self-identification capability, and there are no widely used mechanisms to enable the WBAN to detect node placement. In addition, requiring patients to perform complicated setup procedures on a daily basis is impractical, and relying solely on the wearer’s skill to place labeled WWSNs is at best unreliable. Nonetheless, simplicity is crucial for the ideal self-worn system. For these reasons, designing a system of WWSNs with placement-awareness capabilities becomes highly desirable. Our proposed solution lies in adding an atmospheric air pressure sensor (AAPS), an MEMS device similar in size to accelerometers and other MEMS sensors widely used in WBANs today, to each WWSN. AAPSs would enable the WBAN to measure and track the air pressure at each WWSN location. Minimal patient intrusiveness is achieved, since the wearer would no longer have to worry about accidentally swapping or muddling up WWSNs—the WBAN would automatically identify placement of each WWSN relative to one another in absolute coordinates longitudinally along the length of the body, each time the nodes are replaced, in order to dynamically assign their corresponding tasks. Nodes worn around the body already frequently consist of identical and interchangeable hardware to minimize design and manufacturing cost, so this advantage can be used to eliminate the need to design specific nodes for specific locations.

Many long-term health and medical monitoring applications exist which could greatly benefit from knowing the placement location of each WWSN. One such application this paper explores experimentally is the enhancing of on-body accelerometer-based fall detection systems with sensor node locations. This is to enable the WBAN to make a decision on whether a fall occurred not only based on impact detected by accelerometers, but also on the patient’s current body position for a more informed picture of the patient’s condition.

This paper expands with an analysis of our technique, first demonstrated in [1], using our WBAN platform [2] to the following.
1) Experimentally verify a new scheme enabling WWSNs to automatically perform node localization and limb recognition, by determining and tracking the vertical arrangement of WBAN nodes.

2) Quantify the scheme’s reliability by statistically analyzing the output of the AAPS to ensure accurate decisions with confidence intervals (CIs) >95%.

3) Improve accelerometer-based fall detection performance by enhancing the classical impact detection mechanism with limb position information and patient body state.

The rest of this paper is organized as follows. Section II explores related works in the area of sensor node localization, limb position tracking, and patient fall-detection systems. Section III experimentally verifies our proposed WWSN placement verification and limb recognition scheme. Section IV applies this scheme to enhance an on-body fall detection system to reduce Type I (false-positive) detection errors. Section V concludes this paper.

II. RELATED WORK

Many efforts have been made to improve WWSN location detection, although the primary motivation behind the majority of the studies pertained to improving data transmission and routing between wireless nodes [3]–[6]. These techniques are tailored to general wireless sensor networks (WSNs) and assume tens or hundreds of nodes, as opposed to at most a handful of nodes in WBANs. Using radio signal strength or other ranging techniques to perform area or distance-based localization only provides relative node locations if anchor nodes or beacons are not used, which may not be feasible given that a WBAN may move between different locations. Relative positioning may be sufficient to generate logical topologies for routing, but absolute positioning is required to identify and locate WWSNs in physical space. Schemes based on self-organizing maps [7], [8] also require such anchors for absolute positioning.

Regarding pattern matching techniques, such as in [9], limbs are matched to a set of known placement positions. Here, mixed supervised and unsupervised learning techniques are used on captured accelerometer data to correctly classify the body region of a placement, yielding an average 89% accuracy. However, the attained accuracy depended heavily on the limb measured. More importantly, requiring 30 min of motion data plus additional off-body processing requirements makes this scheme unsuitable for real-time limb identification. Off-body limb recognition methods have also been explored, where the face and upper-body limbs are recognized and tracked using a video camera in real time [10], [11]. However, due to the intensive image processing required for limb detection, extensive computing power is required to support this technique, and the need for powerful off-body equipment limits the technique’s effectiveness for long-term monitoring WBAN applications. However, using small-scale geospatial and hypsometric information in the Earth’s atmospheric air pressure distribution to position WBAN sensor nodes (placed less than a few meters apart) remains unexplored. By applying this idea, we can map WWSN placement without the need for stationary off-body hardware. To demonstrate the possibility and feasibility of implementing this idea using commercially available pressure sensors, we recently presented a basic proof-of-concept WBAN platform [1].

On the study of fall detection systems, where an off-site caregiver can be notified if the patient being monitored suffers from a fall, most proposed systems leverage one of two classes of concepts. The first class involves on-body motion sensing, where falling is inferred by characteristic patterns in body acceleration and motion [12]–[18]. The second class involves off-body monitoring using video cameras [10], [11], [19]–[21], where limb recognition and tracking is utilized to monitor the patient’s motion. Both classes have their own advantages, but also significant drawbacks and deficiencies which have thus far prevented mass end-user adoption [22].

The first class of concepts relies on spikes or patterns in readings of one or two accelerometers and/or gyroscopes mounted on a patient’s body to trigger predefined thresholds and deduce falls [12]–[16]. However, many common activities, for example, sitting down on a chair, could produce false-positives due to similar acceleration characteristics, even though a fall has not occurred [13], [22], limiting the confidence in relying solely on this technique to deduce actual falls. More critically, many papers have demonstrated that such a system alone would result in a significant quantity of false-negatives, that is, falls that go about undetected. As well, variations of this concept to reduce the false-detection of falls have been attempted. Simple variations include monitoring the patient for seconds or minutes after acceleration spikes to determine if he/she gets up immediately after [23]. However, in an actual fall emergency, waiting for the patient to get up may waste valuable time. In another variation, machine learning is incorporated alongside radio frequency location tags placed around the body [24]. However, the authors acknowledge that this approach is still deficient in differentiating “fall-like” events from slow falls.

Concerning the second class of concepts, namely off-body video monitoring, while limb recognition has been demonstrated with a high degree of accuracy [10], [11], [20], [21], [25], [26], aside from computing power considerations related to video processing, limb recognition using video feeds has been dismissed time after time due to privacy issues surrounding the continuous video recording of the patient [27], [28]; studies based on such a system have been rejected even by focus groups due to being too intrusive. As well, since cameras require off-body installation, the system’s operation is limited to the rooms in which the cameras are installed [19]. Thus, such a system has limited portability in long-term monitoring; for example, such a system could not follow patients outside of their homes.

As we can see, both classes of fall detection systems have significant drawbacks preventing mass adoption thus far. Accelerometer-based systems lack accuracy and reliability due to frequent false-positives and false-negatives, and video camera-based systems are hindered by significant privacy concerns. The inherent portability advantage of self-contained on-body solutions places them closer to real-world use. Furthermore, an on-body fall detection scheme can even be incorporated into a WBAN already worn by a patient for other long-term monitoring purposes, such as Parkinson’s disease tremor.
monitoring. We propose enhancing accelerometer-based fall detection schemes by augmenting the known position of WWSNs and their affixed body limbs. The added information of whether the patient is standing up or lying down in the period immediately following acceleration spikes would quickly enable a remote caregiver to make a more informed decision on whether or not the patient requires assistance, and reduce the common problem of false-positive detections.

III. WWSN LOCATION RECOGNITION USING AAPS

A. Localization Technique Overview

The core of our work is based on experimentally exploring and validating geospatial information in the context and size-scale of WBANs. Our new localization technique leverages the geospatial air pressure distribution in the Earth’s atmosphere, described by the following expression of the hypsometric equation [29]:

\[ p = p_0 (1 - (Lh/T_0)) (gM/RL) \]  

(1)

We measure atmospheric pressure \( p \) (in Pascals) at altitude \( h \) (in meters), given sea level atmospheric pressure \( p_0 \) (in Pascals) and other constant parameters,\(^1\) while noting that air pressure decreases as altitude increases. The International Standard Atmosphere model assumes a constant \( L \) between 0 and 11 km in altitude, enabling (1) to be valid for at-home applications. To overcome the variation of atmospheric air pressure measurements with time and weather, we compare the instantaneous pressures around the body to determine the vertical arrangement and locations of the nodes on a scale relative to the wearer. This is possible by assuming that the number of nodes in the WBAN remains the same, enabling the mapping of the expected node locations with an ordered list of node locations measured; the node with the highest air pressure is identified as the node placed at the lowest position. This procedure is almost instantaneous and is only required each time the WWSNs are placed. Detecting removal of WWSNs from the body could be accomplished by devices such as a heart rate sensor, but is outside the scope of this study.

To demonstrate and evaluate our scheme against a practical application which would benefit from WWSN location awareness for limb recognition, we adopt our WBAN specified in [2], which monitors tremors and dyskinesia symptoms in Parkinson’s disease patients. The WBAN (see Fig. 1) consists of WWSNs mounted on a patient’s body and a data aggregation base station node, all consisting of standard Crossbow TelosB motes (see Fig. 2). Specifically, the WWSNs are to be placed on the left wrist, where a watch is typically worn, and the left calf, resting just above the ankle. In addition to sensors required by the primary application of the WBAN (for example, three-axis accelerometers), each WWSN has been fitted with a Bosch BMP085 AAPS for localization and limb position tracking. This small, low-cost, low-power device can detect air pressure differences of <3 Pa in ultrahigh resolution mode, translating to approximately 25 cm in altitude change, and advertises <1 Pa resolution with software averaging. The AAPS draws 12 \( \mu \)A at 1.8–3.6 V if sampled at 1 Hz at 25 °C; assuming an upper bound case where 10 Hz sampling translates to a 10× power consumption, each AAPS would consume about 0.43 mW. This would only minimally tax a typical CR2032 WWSN battery, which provides 675 mWh. We note that MEMS sensor technology evolves very rapidly, and the precision of the AAPS is the key factor in determining the minimum confidently detected WWSN spacing.

To determine WWSN placement through height inference, each node transmits air pressure \( p \) and temperature \( T \) readings together with data collected for the WBAN’s primary application to the base station. In our setup, a personal computer aggregates all sensor data and performs postprocessing using MATLAB. Although pressure readings can be compared directly for WWSN localization purposes, altitudes \( h \) at each node location can also be deduced using (1) from \( p \) by obtaining \( p_0 \) from an external source; in our setup, we opted to use Environment Canada’s weather report.

B. Localization Technique Validation and Results

The experimental validation of our technique consists of the following major procedures to evaluate the system’s performance in detecting the changes in height required for WWSN localization and limb position tracking.

1) Selecting appropriate AAPS sampling parameters (one sensor, one position).
2) Ensuring that the selected AAPS can accurately and reliably detect small-scale changes in air pressure, applicable along the height of a human body (one sensor, two positions).

3) Examining and correcting for intrinsic differences between two different AAPSs, to ensure that readings from one can be compared with readings from another (two sensors, one position).

4) Combining the previous procedures to enable the WBAN to measure the air pressure at two limb locations without reusing the same sensor (two sensors, two positions).

While data were manually captured at controlled times for the purpose of validating our experiment, we expect a commercial-grade WBAN to continuously sample the AAPS and utilize a rolling window to repeatedly perform the statistical testing described in this section to monitor the position of WWSNs in the WBAN.

C. Selecting Appropriate Pressure Sensor Sampling Parameters (One Sensor, One Position)

The proposed system aims to expedite the process of accurately verifying WWSN placement while reducing power consumption. On one hand, the accuracy of the verification process depends on the raw AAPS readings output, whose error margins (noise), in turn, depend on the sampling rate. Empirical results obtained through our WBAN setup reveal that by employing the highest resolution mode of the AAPS, a 10-Hz sampling rate suffices to minimize noise and reduce power consumption by not overloading the microprocessor unit (MCU) through oversampling. However, a suitable sampling time window must be obtained in order to optimize the accuracy of the WWSN placement verification assessment.

To this effect, we placed one node on a stationary surface and sampled the AAPS readings for one hour. Simple visual inspection and comparison with Environment Canada weather reports corroborated either steady air pressure variations (increasing or decreasing) or a stable output, depending on the current weather conditions. However, our approach is not impacted by this, because the time scale of the WWSN placement verification process is too short compared to the length of time it takes for atmospheric air pressure changes to have any effect on the system’s accuracy. It follows that a placement verification process subject to rapid, artificial changes in atmospheric air pressure is prone to inaccuracies because this circumstance skews the probability distribution function (PDF) of the readings’ error margin. In other words, the proposed scheme enhances location verification reliability by ensuring that the statistical analysis is performed over data samples unambiguously described by a probability distribution, as detailed shortly.

By taking 1 h of pressure data readings where the sea level air pressure remained stable, and by examining window sizes (subsets of this data) between 1 and 60 s, the mean and spread of pressure readings remained very similar throughout this range, as depicted in Table I. By characterizing the PDF and cumulative distribution function (CDF) of the data samples at hand, we can define CIs that can be referenced to determine pertinent data sampling windows that maximize the accuracy of the system’s assessment process. We examine the goodness of fit (GOF) of the data from each window size against a Gaussian distribution with 95% CI. Fitting the data to common distributions using GOF tests showed that a Gaussian distribution had the best fit. From Table I and the probability plot in Fig. 3, we can see that sampling windows of 2, 3, 5, and 10 s produced readings that could be confidently approximated by a Gaussian distribution, that is, their p-values were > 0.05. Furthermore,
the 3-s sampling window returned the highest $p$-value, meaning this sampling window would be most preferable, in order to ensure that the error estimation process corresponds with a Gaussian PDF describing the actual data samples output by the sensor. Otherwise, employing an error estimation scheme for a data stream with mismatching PDF would invalidate the accuracy of our approach. Repeating this analysis with two more sets of pressure data also produced the same findings, where the 3-s sampling window gave the highest $p$-value.

The different sampling window trials shown in Table I and the corresponding pressure reading distributions gives us a good reference point to determine the length of the sampling window based on the GOF results. With too short of a sampling window, too few data points are available for an accurate fit. However, if we take measurements for too long, overall fluctuations in atmospheric air pressure due to the weather would skew our readings, thus limiting the accuracy of our proposed approach.

D. Verifying Assessments of Height Measurements (One Sensor, Two Positions)

In this section, we describe the verification process to ensure that our hardware can accurately and reliably detect the small-scale changes in air pressure representative of heights along the human body, in accordance with the results obtained and described in Section III-C. This is achieved by placing one AAPS at two locations spanning a controlled vertical distance apart, and by ensuring that the pressure measurements at the two locations can be distinguished from one another if the obtained measurements statistically remain within the CI. Here, we first utilize only one AAPS to negate the intrinsic hardware differences between two different sensors. We demonstrated this technique and reported preliminary results in [1]. In a practical WBAN, we need two WWSNs to obtain measurements at two positions, as described and examined in the next sections. We placed the single sensor at two baseline heights, defined as 0 cm (position I), and at 60 cm above position I (position II) and obtained pressure data at the two positions. The 60 cm height difference was selected as a starting point indicative of the typical minimum distance between two limb positions we expect our system to monitor, based on a two-WWSN WBAN with one arm node and one leg node. We examine 3-s data portions using two-sample T-tests. Since identical sensors were used, we assume equal variances between the two sets of data. First, we compare one set of sample data from position I against a set from position II, and repeat the test ensure reproducibility. Next, we compare sample data taken from the same position against each other to ensure that same position data are not falsely detected as being different. A small $p$-value enables us to reject the null hypothesis; that is, there is a statistically significant difference in height estimates at the two positions.

From Table II, we can see that for all three trials, placing the sensor at 60 cm altitude differences returned pressure difference measurements of on average 8–10 Pa, with an estimated difference of 7–12 Pa with a 95% CI. Furthermore, the two-sample T-tests returned $p$-values of 0 for all three trials, confirming that the height estimate at position I is statistically different from that at position II with $\mu > 99.9\%$ CI. This means that the sensor readings from location 1 differ enough from location 2 to enable the system to detect the changes in air pressure, and thus height, that we require. From Table III, comparing pressure data taken from the same positions against each other, the two-sample T-tests for all three trials returned $p$-values $>0$. This means, as expected, that the results are insufficient to falsely identify different height assessments given the same position. Repeating this experiment with more data provided agreeable results; further trials, including data collected on different days and at different physical locations, all corroborated $p$-values of 0 in Table III, supporting that data from the two positions are statistically distinguishable.

E. Verifying Assessments of Height Measurements (Two Sensors, One Position)

In this section, we describe the process of verifying that two different sensors measure the same pressure when placed in the same position. During initial experimentation, we discovered that AAPSs placed together at the same altitude reported...
pressure readings offset from one another. Moving both AAPSs the same distances vertically produced the same offsets. This showed a constant offset and implied that the differences in response between otherwise identical AAPSs were due to insufficient precision in the eleven 16-bit factory calibration coefficients that are unique to each sensor, possibly because the sensor was designed for measuring more macroscale air pressure readings. This realization highlights the importance of understanding the operation of AAPSs for measuring fine-grain, human-scale height differences at the highest possible resolution. After more testing with a third AAPS, comparable constant offset observations were made. These offsets relative to each sensor were found to not change over time. Thus, this one-time constant offset correction calibration process is important in enabling meaningful comparisons of readings between different AAPSs, and thus a reliable height-based WWSN placement estimation system.

To substantiate this claim, we place two AAPS-equipped WWSNs side-by-side (at the same altitude) and examine the mean and spread of the pressure data from each node. Using the 3-s, 10-Hz sample window determined previously, we can see in Table IV that applying a two-sample T-test (assuming equal variances) returned differences in measurements between two AAPSs placed at the same position of on average 40–43 Pa, with an estimated difference of 37–45 Pa with a 95% CI. Clearly, without offset correction, any comparisons made between different sensor hardware are prone to error, as the offset is approximately four times larger than the change in pressure we saw over a 60-cm vertical distance. To ensure that we can apply this correction factor just once and be able to meaningfully compare pressure readings between different hardware, we ensure that this offset is indeed a constant offset, that is, the offset does not change with altitude or over time. This was accomplished by repeating the experiment at different altitudes over the height of a typical human body, and examining the pressure offset between the two sensors. Measurements obtained between two nodes at the same location revealed very similar estimates, and that the offset for our two particular AAPSs remained at approximately 40 Pa. This confirms that the offset can be treated as being constant for the purposes of our approach, thereby enabling us to compare pressure measurements between sensors so long as this offset is accounted for.

F. Validating Assessments of Height Measurements in a WBAN (Two Sensors, Two Positions)

In this last step, we combined our previous approaches to estimate air pressure measurements at two different locations. Because verifying the correct placement of WWSNs on limbs requires the ability to measure the air pressure at each location simultaneously, we must validate that using two sensors to measure pressures at two locations produces data comparable to those described in Section III-D, where the output of a single sensor was gauged at two positions (one case at a time). Again, we utilize a 3-s sampling window as per the results presented in Section III-C.

Using the same two-sample T-test and assuming equal variances as per the procedure in Section III-D, as well as constant offset as per Section III-E, the results displayed in Table V show that the pressure differences between the two positions are indeed statistically significant, and the test verifies that the two positions are indeed different. Also, the 7–15-Pa estimate for the pressure difference at a 95% CI is very comparable to the 7–12-Pa estimate for the pressure difference with 95% CI at 60 cm apart observed in Section III-D; see Table II. Performing more trials produced similar pressure difference estimates. Thus, the test demonstrated that the constant offset correction is successful, and valid comparisons can be made between pressure measurements from two nodes. Empirical CDF plots for each of the three trials show the measured pressure differences between the two nodes at the two positions (60 cm apart).

By determining and accounting for the differences in sensor hardware in a one-time calibration process, where the AAPSs are placed at the same vertical location, to correct the constant
nodes to perform ranging. One limitation of the approach is its inability to distinguish between different nodes attached at the same height on the body, for example, a WWSN attached to the left arm and another attached to the right arm. An additional technique would be required to identify left and right nodes. Notwithstanding this, since the human body is slender, and more WWSNs are typically distributed along the height of a body, by being able to self-identify WWSNs at different heights, we have reduced the number of nodes requiring manual identification to “left” and “right” nodes, which is far more convenient for the patient.

IV. ENHANCING ACCELEROMETER-BASED FALL DETECTION SCHEMES WITH LIMB POSITION TRACKING

A. Overview of Fall Detection Experimental Setup

In a typical on-body fall detection system, accelerometers are fitted in WWSNs to capture x-, y-, and z-axis limb acceleration, and elementary fall detection techniques look for “falls” by monitoring acceleration magnitude peaks due to impact [12], [13], [15], [16]. However, as explained in Section II, motion from certain daily activities such as sitting down on a chair often produces large z-direction acceleration spikes and could be mistaken as a “fall” [13]. Since traditional on-body schemes lack contextual awareness, the expected detection accuracy based on impact magnitudes alone cannot be entrusted for remote long-term at-home fall monitoring.

In this section, we apply our WWSN placement recognition technique to improve such an on-body fall-detection WBAN. Such systems typically comprise of one or two WWSNs placed on a patient’s body for long-term monitoring, which makes our localization scheme in Section III a good candidate for providing enhanced contextual awareness. We introduce limb position awareness to monitor the patient’s body movements in time intervals surrounding any detected impact. With our enhancement, a WBAN continuously tracks and monitors the instantaneous air pressure at each limb to deduce the patient’s physical state, immediately after significant accelerometer activity is detected that could indicate a “fall-like” event. By comparing pressure differences against the known WWSN placement topology, the WBAN can examine the position of the arm relative to the leg, and deduce if the user is upright (standing or sitting up, where the nodes are at different vertical positions), or lying down (where the nodes are vertically at the same position). With this contextual information, we expect to be able to reduce false-positive detections (see Section IV-B), where falls were detected but no fall had occurred. To demonstrate that this scheme is beneficial to an on-body fall detection system, we scope our study to replicate the variety of typical daily at-home activities the user being monitored is expected to encounter, to observe how our proposed enhancement responds in determining the patient’s context, compared to a system relying solely on accelerometer impact response. Specifically, the tasks studied and replicated in Section IV-C include walking, traversing stairs, sitting down, lying down, and a fall to the ground. The change in acceleration and air pressure at each WWSN is recorded and examined.

<table>
<thead>
<tr>
<th>Table V</th>
<th>Comparing the Measured Pressures Distribution With Two Sensors at Two Positions With Constant Offset Correction, Using a Two-Sample T-Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node / Position</td>
<td>N [#]</td>
</tr>
<tr>
<td>N1 @ 0cm</td>
<td>30</td>
</tr>
<tr>
<td>N2 @ 60cm</td>
<td>30</td>
</tr>
<tr>
<td>Estimate for difference μ(N2) - μ(N1)</td>
<td>12.87</td>
</tr>
<tr>
<td>95% CI for difference: (10.63, 15.11)</td>
<td></td>
</tr>
<tr>
<td>T-Test of difference = 0 (vs not =)</td>
<td></td>
</tr>
<tr>
<td>T-Value = 11.50 P-Value = 0.000 DF = 58</td>
<td></td>
</tr>
<tr>
<td>N1 @ 0cm</td>
<td>30</td>
</tr>
<tr>
<td>N2 @ 60cm</td>
<td>30</td>
</tr>
<tr>
<td>Estimate for difference μ(N2) - μ(N1)</td>
<td>10.93</td>
</tr>
<tr>
<td>95% CI for difference: (8.58, 13.29)</td>
<td></td>
</tr>
<tr>
<td>T-Test of difference = 0 (vs not =)</td>
<td></td>
</tr>
<tr>
<td>T-Value = 9.29 P-Value = 0.000 DF = 58</td>
<td></td>
</tr>
<tr>
<td>N1 @ 0cm</td>
<td>30</td>
</tr>
<tr>
<td>N2 @ 60cm</td>
<td>30</td>
</tr>
<tr>
<td>Estimate for difference μ(60cm) - μ(0cm)</td>
<td>10.17</td>
</tr>
<tr>
<td>95% CI for difference: (7.83, 12.50)</td>
<td></td>
</tr>
<tr>
<td>T-Test of difference = 0 (vs not =)</td>
<td></td>
</tr>
<tr>
<td>T-Value = 8.72 P-Value = 0.000 DF = 58</td>
<td></td>
</tr>
</tbody>
</table>

offset analyzed in Section III-E, the same pressures are measured by the two separate WWSNs when placed at the same altitude. Thus, it is possible to draw accurate and meaningful comparisons between the air pressure measurements at each limb, thereby enabling the WBAN to pinpoint its WWSNs.

G. Localization Technique Discussion and Limitations

By examining altitude differences between WWSNs, we have introduced and demonstrated a new scheme for WWSN localization, by leveraging fine-grain hypsometric information of the Earth’s atmosphere. Given the physical topology of the WBAN, the scheme confidently identified which node was attached to which limb based on the altitude information of each WWSN. The placements at each height corresponded to placing WWSNs on the head, arm, and/or leg. This scheme assumes the WWSN placement discovery, and verification process takes place while the patient is upright to maximize the distances between the nodes, and thus improve detection accuracy. We anticipate that this will not limit the real-life usefulness of this system; as discussed in Section III, node localization for limb recognition and tracking is only required each time the patient takes off and replaces the WWSNs from his or her body. In our experiment, we tested WWSNs at 60 cm apart, indicative of the minimum expected distance between a patient’s arm/wrist and lower leg. The larger the distance apart, the higher the accuracy of the system. Since beginning our study, Bosch has released the BMP180 AAPS to replace the BMP085 AAPS we utilized in this study, which increases detection accuracy from 3 Pa (25 cm air column) to 2 Pa (17 cm air column) in ultrahigh resolution mode, at comparable size and cost. Prior to selecting the BMP085 AAPS, we wished to perform this study with the VTI SCP1000 AAPS which advertises a 9 Pa detection accuracy. However, this AAPS was discontinued in the months before our study began.

In contrast to traditional WWSN localization techniques surveyed in Section II, our approach does not rely on having a large number of nodes to perform localization, nor stationary beacon
The WBAN and experimental configuration in Section III, consisting of one WWSN attached to the arm, and another attached to the leg (see Fig. 1), was reused. This is to demonstrate that a Parkinson’s disease limb tremor monitoring system, such as [2], could be easily upgraded with fall-detection capabilities, without additional WWSNs or moving nodes around. For a pure fall-detection WBAN disregarding primary application sensor placement, it is worth noting that studies on sensor placement to record acceleration due to falls has so far been inconclusive [18]; some have suggested behind the ear [12], the trunk [13], or the head and waist [15] areas as being the optimum locations for a fall sensor. Our proposed approach aims to increase the sensitivity and performance of on-body fall detection and allow the primary application of the WBAN to dictate the placement of WWSNs.

B. Fall Detection Hypothesis Testing

We define the following fall detection hypotheses.

1) $H_0$ (null hypothesis)—A fall was detected (the two WWSNs are found to be at the same vertical position).

2) $H_1$ (alternative hypothesis)—No fall was detected (the two WWSNs are not found to be at the same vertical position).

These hypotheses aid in describing the four possible outcomes.

1) A fall was detected, and there has indeed been a fall (true-positive, desired outcome, accept $H_0$).

2) A fall was detected, but there was no fall (false-positive, undesired outcome, Type I error from falsely rejecting null hypothesis).

3) A fall was not detected, and there had indeed been no fall (true-negative, desired outcome, reject $H_0$ correctly).

4) No fall was detected, but there was a fall (false-negative, Type II error from falsely not rejecting null hypothesis).

The hypotheses are formed in this order to ensure that the system only concludes that no fall has occurred if it can confidently be sure that the null hypothesis can be rejected. This is because an undetected fall (a false-negative) has more fatal consequences than one where no fall has occurred but an alarm is triggered (a false-positive).

We further define the probability that the patient requires assistance and caregiver attention $P(H_0)$ as the intersection of $P(\text{fall})$, the probability that an impact or free-fall has occurred as detected by an accelerometer, and $P(\text{lyingdown})$, the probability that the patient is lying down, as detected by AAPSs, in the time immediately following:

$$P(H_0) = P(\text{fall}) \cap P(\text{lyingdown}).$$  \hspace{1cm} (2)

In a nutshell, our proposed fall detection enhancement considers both $P(\text{fall})$ and $P(\text{lyingdown})$, as opposed to traditional on-body systems that rely solely on $P(\text{fall})$. The WBAN is to make an assessment based on the occurrence of AAPSs at the arm and leg reporting similar altitude to estimate $P(\text{lyingdown})$ (implying that the patient is lying down) within a margin of error, given that an accelerometer has indicated a fall event based on the magnitude of impact or free-fall $P(\text{fall})$. Falls requiring attention based on $P(\text{fall})$ alone have been previously studied in detail in [12], [13], [15], and [16]. Thus, this section will focus on the performance of the $P(\text{lyingdown})$ enhancement, and whether or not the enhancement can accurately and reliably detect that a patient is lying down as a result of the daily at-home activities studied. We quantify our system’s performance in detecting a patient as “lying down” by sampling 3-s windows of pressure data immediately after the accelerometer observes spikes from the replicated scenario, and performing two-sample T-tests between the two WWSNs for each data set (trial). Depending on the scenario, the $p$-value should either conclude that the two nodes are at different altitudes (the patient is not lying down), or that the nodes are not at different altitudes, inferring that the patient is lying down. The closer the $p$-value is to 0, the more confident we can be that the patient is not lying down.

C. Fall Detection Enhancement Experimental Results

1) Scenario 1 (Walking): In a fall detection system, aside from staying still, walking is likely the most elementary and common movement type. Our subject replicates typical walking on level ground, representative of ordinary daily activities around the home. As shown in Fig. 6,2 each footstep results in an acceleration spike 0.5–2 g in magnitude. The two-sample T-tests (see Table VI) estimated a 7–14 Pa difference in pressure.
2) Scenario 2 (Walking Up/Down Stairs): The walking scenario was also studied on a staircase, to recognize that falls while walking are also likely while traversing stairs [30]. Scenario 2A describes the walk up, and Scenario 2B describes the walk down. Performing two-sample T-tests (see Table VI) gave a 4–15 Pa estimated difference in pressure between the two positions, with a \( p \)-value of 0 for both scenarios, once again indicating a true-negative case, that the arm and leg are at different vertical positions, with absolute certainty. The results also infer that the arm and leg are closer together compared to Scenario 1, which is valid because of the leg motion involved in climbing stairs. As an aside, while the accelerometer sees similar motion data in both walking scenarios, the difference due to walking up and down a flight of stairs is clearly observed in Fig. 7, further aiding in the contextual awareness and determining the patient’s motion pattern.

3) Scenario 3 (Sitting Down): In this scenario, we analyze the response of the system due to sitting down onto a chair, and standing up. Fig. 8 shows the data acquired from our test subject repeatedly sitting down and standing up. Impact between the subject and the chair is clearly distinguishable in the accelerometer data, which would be used to trigger the location measurements. Two-sample T-tests (see Table VI) estimate a 8–16 Pa difference in pressure between the arm and leg positions, with a \( p \)-value of 0 for both scenarios, again indicating with very high confidence that we can reject the null hypothesis as desired, as the user is not lying down. As well, from the pressure and inferred altitude, we can differentiate between periods when the user is standing up and sitting down as well, since the distance between the arm and leg nodes narrows significantly when the user sits down.

![Fig. 7](image1.png) Scenario 2: Walking Up/Down Stairs—Arm and leg acceleration, air pressure, inferred altitude. While AAPS readings reflected gaining and losing altitude to provide context, once again, the arm and leg nodes remain distinctively different from each other aside from small fluctuations.

![Fig. 8](image2.png) Scenario 3: Sitting Down—Arm and leg acceleration, air pressure, inferred altitude. Arm and leg movement is clearly evident; the nodes moved closer together when the wearer sat down. However, an average difference in AAPS readings is still present, implying that the sensors are still physically apart, and that the wearer is not lying down.
Fig. 9. Scenario 4: Lying Down—Arm and leg acceleration, air pressure, inferred altitude. The period in which the test subject was lying down can clearly be seen by the overlapping arm and leg node AAPS readings. This overlap suggests that the two nodes are vertically at the same height.

4) Scenario 4 (Lying Down): This scenario involves lying down onto a bed from an upright position. The accelerometer trace in Fig. 9 illustrates the fall. Examining the pressure data during the period the user is lying down (when the AAPSs from the two WWSNs become placed at the same altitude), we observe a fast response as the two traces converge to the same pressure and altitude readings between 7 and 15 s. Two-sample T-tests in this region estimate a 0–5 Pa difference in pressure between the arm and leg positions with 95% CI (see Table VI), and \( p \)-values \( > 0 \) demonstrate that, as expected, we cannot from this data statistically reject the null hypothesis (that the arm and leg are at different heights, that there was no fall). Similar to Scenario 4, this would imply a possibility of the patient lying down. This is consistent with a visual examination of Fig. 10, where the arm and leg node pressure traces clearly converge. Since the WBAN is no longer confident that the patient is still upright, in considering both \( P(fall) \) and \( P(lying\_down) \), if an accelerometer-detected “fall” preceded this change in arm and leg position, a caregiver can be immediately alerted of a potential situation. A closer examination of both acceleration magnitude and air pressure convergence shows strong a similarity to the data obtained by lying down in Scenario 4.

5) Scenario 5 (Fall Onto Ground): In this scenario, our test subject replicates a fall onto the ground, from an upright standing position onto a hardwood floor. Already, we notice in Fig. 10 that a basic fall detection system which relies solely on acceleration thresholds would not be reliable, as the magnitudes here are quite similar to those even in the walking case in Fig. 6. Two-sample T-tests in 3-s data windows immediately succeeding an accelerometer spike estimate a 0–6 Pa difference in pressure between the arm and leg positions with 95% CI (see Table VI), and \( p \)-values \( > 0 \) demonstrate that again, we cannot statistically reject the null hypothesis (that the arm and leg are at different heights, that there was no fall). Similar to Scenario 4, this would imply a possibility of the patient lying down. This is consistent with a visual examination of Fig. 10, where the arm and leg node pressure traces clearly converge. Since the WBAN is no longer confident that the patient is still upright, in considering both \( P(fall) \) and \( P(lying\_down) \), if an accelerometer-detected “fall” preceded this change in arm and leg position, a caregiver can be immediately alerted of a potential situation. A closer examination of both acceleration magnitude and air pressure convergence shows strong a similarity to the data obtained by lying down in Scenario 4.

D. Fall Detection Enhancement Discussion and Limitations

This enhancement demonstrated reliable detection of a wearer’s state during the different at-home activities replicated, for deducing \( P(living\_down) \) in reducing false-positive detections. From our results, the WBAN successfully differentiated between an upright position and lying down. While the AAPSs alone were unable to further distinguish between specific different upright positions (standing versus sitting), we observe that the usefulness of a contextually aware WBAN is highlighted in a fall detection application; a much better decision on the
patient’s condition can be made simply by knowing if a patient is lying down. As explained, in some of these scenarios, relying solely on accelerometer data would make it difficult to distinguish between a “slow fall” and other fall-like activity, as in [24]. Moreover, it has been identified that many elderly people “fall” onto a chair when sitting down due to reduced muscle strength with old age [13]. This results in higher acceleration peaks than analyzing young adults sitting down, who have much greater control over the speed of their body motions; depending on how the patient sits on a chair, the acceleration profile could be similar to an actual fall. With our proposed enhancement, by considering both the $P(\text{fall})$ explored extensively in previous works and $P(\text{lyingdown})$, augmenting arm and leg position information clearly shows that after such a “fall” on a chair, the WBAN can now be aware that the patient is still upright and not lying on the ground, thus reducing false-positive estimates of $P(H_0)$ when compared to previously studied on-body fall detection systems where $P(H_0)$ was solely deduced by $P(\text{fall})$.

We can foresee some cases where augmenting limb position information would not help reduce the probability of false-positive detection. From our experimental data, we found it difficult to distinguish activities for a patient lying down and falling using either accelerometer data or altitude information. Both the lying down scenario and emulated fall produced similar accelerometer peaks; comparing the accelerometer data from the arm node at time 4–6 s in Figs. 9 and 10 with [13, Fig. 1A], both cases generate accelerometer responses that would indicate a fall, although lying down on a bed is not actually a fall. While beyond this specific case, our scheme has demonstrated improvement in false-positive detection, to further improve our proposed enhancement, we could extend the scope of our study to the fine-tuning of T-test parameters, for example, the acceptable $p$-value threshold at 95% CI to determine if the nodes are at different positions. We could also further examine the instantaneous impact acceleration characteristics, or expand on the types of contextual information provided to the WBAN, for example, by incorporating additional sensors such as heart rate to even better distinguish between body states.

V. CONCLUSION

We have presented and experimentally verified a new approach to determine the location of WWSNs mounted along the height of a patient’s body by measuring and comparing instantaneous air pressures at each node. The spatial information enables the WBAN to automatically identify and map which WWSN is mounted on which limb. We believe this technique is novel because the technique reliably maps a wearer’s limb locations in absolute coordinates longitudinally along the length of the body, without requiring additional nodes or off-body infrastructure. We have experimentally verified the feasibility and practicality of implementing this approach into an existing WBAN designed for long-term at-home patient monitoring in Section III. We have shown that commercially available AAPSs can be utilized to produce reliable and accurate position information. Once the WWSNs are identified, by continuously tracking the limb positions, the WBAN is able to infer basic daily activities, for example, standing and lying down. While a 60 cm separation between two WWSNs, indicative of a patient’s arm and leg limb spacing, was studied, the scheme’s granularity is limited only by the accuracy and precision of the AAPS hardware (see Section III-G). In adapting the localization scheme to an autonomous commercial WBAN with minimal patient intervention, some challenges could include power consumption optimizations (such as adaptive sampling frequency) toward long-term monitoring, and the detection of whether or not WWSNs are currently being worn or their physical placements have changed (see Section III-A).

This scheme enhances the context awareness of WBAN applications such as fall-detection systems, to better preclude falls requiring attention from other “fall-like” activities where the patient is clearly still standing (see Section IV). Augmenting limb position information has enabled our on-body fall detection WBAN to better deduce and classify activities that accelerometer-only systems traditionally detect ambiguously or with a high degree of false-positives (Type I errors). By enabling the WBAN to continuously track the patient’s limb positions, on-body fall detection systems can consider both $P(\text{fall})$ and $P(\text{lyingdown})$ to make more informed decisions on $P(H_0)$ and reduce false-positive detections.

As hardware continues to evolve and higher performance sensors are developed, this scheme shall benefit from more precise pressure data, but in the meantime, filters could be employed to reduce noise, as long as no significant MCU overhead is introduced, producing a further tradeoff between power consumption and speed. Since the AAPSs simply add an extra stream of pressure data at each WWSN, transmitted easily over IEEE 802.15.4 in our prototype WBAN platform, we do not anticipate wireless channel limitations when adapting the system to Bluetooth, Bluetooth Low-Energy, or other WBAN protocols. This scheme could even be extended to traditional WSNs (see Section II) to explore collaborative localization with different sensors and radio signal-based area and distance-measuring localization schemes.

Overall, we believe this new technique has a strong promise in delivering accurate and reliable WWSN localization and limb recognition and monitoring to the m-health field.

REFERENCES


Wireless Body Area Network Node Localization Using Small-Scale Spatial Information

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Abstract—We present a new scheme to automatically identify the locations of wearable sensor nodes in a wireless body area network (WBAN). Instantaneous atmospheric air pressure readings are compared to map nodes in physical space. This enhancement enables unassisted sensor node placement, providing a practical solution to obtain and continuously monitor node locations without anchor nodes or beacons. To validate this localization scheme, a statistical analysis is conducted on a set of air pressure sensors and a prototype WBAN to examine the performance and limitations. Based on a 60 cm separation between nodes, indicative of the expected separation between limbs and placement positions along a patient's body, the measurements consistently exceeded p-value reliability within a 95% confidence interval. We also present and demonstrate an enhancement aiming to reduce false-positive (Type I) errors in conventional accelerometer-based on-body fall detection schemes. Our statistical analysis has shown that by continuously monitoring the patient’s limb positions, the WBAN would be better able to discriminate “fall-like” motions from actual falls.

Index Terms—Atmospheric air pressure, fall detection, health monitoring, limb tracking, m-health, node identification, sensor placement, wearable sensors, wireless body area network (WBAN).

I. INTRODUCTION

WIRELESS body area networks (WBANs) are increasingly becoming plausible solutions for on-body health monitoring and diverse medical applications. This can be largely attributed to the decreasing physical size and production costs of microelectromechanical systems (MEMS) sensor technology. Existing health monitoring devices fulfill the aim of being apt for long-term use. However, there is a widespread consensus that replacing wired devices with wearable wireless sensor nodes (WWSNs), designed to measure the vital signs of the patient’s body, is more desirable due to the inherent freedom of movement that the wearer gains. These externally worn nodes often take the form of armbands, leg straps, and adhesive pads to allow for easy removal prior to activities such as showering and swimming, where the nodes may otherwise interfere or malfunction. Unfortunately, this added flexibility increases the chance of misplacing WWSNs after a certain activity is finished and they need to be worn again. A patient could muddle up the nodes, causing, for example, the arm node to record leg motion, and vice versa. Depending on the nature of the long-term monitoring and the frequency at which data are analyzed by the clinician or caregiver, node misplacement could yield conflicting data with the expected patterns at the intended node location. For example, a clinician analyzing arm and leg tremors for dyskinesia symptoms in Parkinson’s disease patients may collect inconsistent data if the sensors’ physical placements over the patient’s limbs mismatch their correct target locations.

Currently, WWSNs are typically manually programmed for collecting data consistent with certain locations of a patient’s body, such as an arm or leg. Sensor nodes have limited self-identification capability, and there are no widely used mechanisms to enable the WBAN to detect node placement. In addition, requiring patients to perform complicated setup procedures on a daily basis is impractical, and relying solely on the wearer’s skill to place labeled WWSNs is at best unreliable. Nonetheless, simplicity is crucial for the ideal self-worn system. For these reasons, designing a system of WWSNs with placement-awareness capabilities becomes highly desirable. Our proposed solution lies in adding an atmospheric air pressure sensor (AAPS), an MEMS device similar in size to accelerometers and other MEMS sensors widely used in WBANs today, to each WWSN. AAPSs would enable the WBAN to measure and track the air pressure at each WWSN location. Minimal patient intrusiveness is achieved, since the wearer would no longer have to worry about accidentally swapping or muddling up WWSNs—the WBAN would automatically identify placement of each WWSN relative to one another in absolute coordinates longitudinally along the length of the body, each time the nodes are replaced, in order to dynamically assign their corresponding tasks. Nodes worn around the body already frequently consist of identical and interchangeable hardware to minimize design and manufacturing cost, so this advantage can be used to eliminate the need to design specific nodes for specific locations.

Many long-term health and medical monitoring applications exist which could greatly benefit from knowing the placement location of each WWSN. One such application this paper explores experimentally is the enhancing of on-body accelerometer-based fall detection systems with sensor node locations. This is to enable the WBAN to make a decision on whether a fall occurred not only based on impact detected by accelerometers, but also on the patient’s current body position for a more informed picture of the patient’s condition.

This paper expands with an analysis of our technique, first demonstrated in [1], using our WBAN platform [2] to the following.

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1) Experimentally verify a new scheme enabling WWSNs to automatically perform node localization and limb recognition, by determining and tracking the vertical arrangement of WBAN nodes.

2) Quantify the scheme’s reliability by statistically analyzing the output of the AAPS to ensure accurate decisions with confidence intervals (CIs) >95%.

3) Improve accelerometer-based fall detection performance by enhancing the classical impact detection mechanism with limb position information and patient body state.

The rest of this paper is organized as follows. Section II explores related works in the area of sensor node localization, limb position tracking, and patient fall-detection systems. Section III experimentally verifies our proposed WWSN placement verification and limb recognition scheme. Section IV applies this scheme to enhance an on-body fall detection system to reduce Type I (false-positive) detection errors. Section V concludes this paper.

II. RELATED WORK

Many efforts have been made to improve WWSN location detection, although the primary motivation behind the majority of the studies pertained to improving data transmission and routing between wireless nodes [3]–[6]. These techniques are tailored to general wireless sensor networks (WSNs) and assume tens or hundreds of nodes, as opposed to at most a handful of nodes in WBANs. Using radio signal strength or other ranging techniques to perform area or distance-based localization only provides relative node locations if anchor nodes or beacons are not used, which may not be feasible given that a WBAN may move between different locations. Relative positioning may be sufficient to generate logical topologies for routing, but absolute positioning is required to identify and locate WWSNs in physical space. Schemes based on self-organizing maps [7], [8] also require such anchors for absolute positioning.

Regarding pattern matching techniques, such as in [9], limbs are matched to a set of known placement positions. Here, mixed supervised and unsupervised learning techniques are used on captured accelerometer data to correctly classify the body region of a placement, yielding an average 89% accuracy. However, the attained accuracy depended heavily on the limb measured. More importantly, requiring 30 min of motion data plus additional off-body processing requirements makes this scheme unsuitable for real-time limb identification. Off-body limb recognition methods have also been explored, where the face and upper-body limbs are recognized and tracked using a video camera in real time [10], [11]. However, due to the intensive image processing required for limb detection, extensive computing power is required to support this technique, and the need for powerful off-body equipment limits the technique’s effectiveness for long-term monitoring WBAN applications. However, using small-scale geospatial and hypsometric information in the Earth’s atmospheric air pressure distribution to position WBAN sensor nodes (placed less than a few meters apart) remains unexplored. By applying this idea, we can map WWSN placement without the need for stationary off-body hardware. To demonstrate the possibility and feasibility of implementing this idea using commercially available pressure sensors, we recently presented a basic proof-of-concept WBAN platform [1].

On the study of fall detection systems, where an off-site caregiver can be notified if the patient being monitored suffers from a fall, most proposed systems leverage one of two classes of concepts. The first class involves on-body motion sensing, where falling is inferred by characteristic patterns in body acceleration and motion [12]–[18]. The second class involves off-body monitoring using video cameras [10], [11], [19]–[21], where limb recognition and tracking is utilized to monitor the patient’s motion. Both classes have their own advantages, but also significant drawbacks and deficiencies which have thus far prevented mass end-user adoption [22].

The first class of concepts relies on spikes or patterns in readings of one or two accelerometers and/or gyroscopes mounted on a patient’s body to trigger predefined thresholds and deduce falls [12]–[16]. However, many common activities, for example, sitting down on a chair, could produce false-positives due to similar acceleration characteristics, even though a fall has not occurred [13], [22], limiting the confidence in relying solely on this technique to deduce actual falls. More critically, many papers have demonstrated that such a system alone would result in a significant quantity of false-negatives, that is, falls that go about undetected. As well, variations of this concept to reduce the false-detection of falls have been attempted. Simple variations include monitoring the patient for seconds or minutes after acceleration spikes to determine if he/she gets up immediately after [23]. However, in an actual fall emergency, waiting for the patient to get up may waste valuable time. In another variation, machine learning is incorporated alongside radio frequency location tags placed around the body [24]. However, the authors acknowledge that this approach is still deficient in differentiating “fall-like” events from slow falls.

Concerning the second class of concepts, namely off-body video monitoring, while limb recognition has been demonstrated with a high degree of accuracy [10], [11], [20], [21], [25], [26], aside from computing power considerations related to video processing, limb recognition using video feeds has been dismissed time after time due to privacy issues surrounding the continuous video recording of the patient [27], [28]; studies based on such a system have been rejected even by focus groups due to being too intrusive. As well, since cameras require off-body installation, the system’s operation is limited to the rooms in which the cameras are installed [19]. Thus, such a system has limited portability in long-term monitoring; for example, such a system could not follow patients outside of their homes.

As we can see, both classes of fall detection systems have significant drawbacks preventing mass adoption thus far. Accelerometer-based systems lack accuracy and reliability due to frequent false-positives and false-negatives, and video camera-based systems are hindered by significant privacy concerns. The inherent portability advantage of self-contained on-body solutions places them closer to real-world use. Furthermore, an on-body fall detection scheme can even be incorporated into a WBAN already worn by a patient for other long-term monitoring purposes, such as Parkinson’s disease tremor.
monitoring. We propose enhancing accelerometer-based fall detection schemes by augmenting the known position of WWSNs and their affixed body limbs. The added information of whether the patient is standing up or lying down in the period immediately following acceleration spikes would quickly enable a remote caregiver to make a more informed decision on whether or not the patient requires assistance, and reduce the common problem of false-positive detections.

III. WWSN LOCATION RECOGNITION USING AAPS

A. Localization Technique Overview

The core of our work is based on experimentally exploring and validating geospatial information in the context and size-scale of WBANs. Our new localization technique leverages the geospatial air pressure distribution in the Earth’s atmosphere, described by the following expression of the hypsometric equation [29]:

\[ p = p_0 (1 - (Lh / T_0)^{(gM/R_L)}) \]  

We measure atmospheric pressure \( p \) (in Pascals) at altitude \( h \) (in meters), given sea level atmospheric pressure \( p_0 \) (in Pascals) and other constant parameters,\(^1\) while noting that air pressure decreases as altitude increases. The International Standard Atmosphere model assumes a constant \( L \) between 0 and 11 km in altitude, enabling (1) to be valid for at-home applications. To overcome the variation of atmospheric air pressure measurements with time and weather, we compare the instantaneous pressures around the body to determine the vertical arrangement and locations of the nodes on a scale relative to the wearer. This is possible by assuming that the number of nodes in the WBAN remains the same, enabling the mapping of the expected node locations with an ordered list of node locations measured; the node with the highest air pressure is identified as the node placed at the lowest position. This procedure is almost instantaneous and is only required each time the WWSNs are placed. Detecting removal of WWSNs from the body could be accomplished by devices such as a heart rate sensor, but is outside the scope of this study.

To demonstrate and evaluate our scheme against a practical application which would benefit from WWSN location awareness for limb recognition, we adopt our WBAN specified in [2], which monitors tremors and dyskinesia symptoms in Parkinson’s disease patients. The WBAN (see Fig. 1) consists of WWSNs mounted on a patient’s body and a data aggregation base station node, all consisting of standard Crossbow TelosB motes (see Fig. 2). Specifically, the WWSNs are to be placed on the left wrist, where a watch is typically worn, and the left calf, resting just above the ankle. In addition to sensors required by the primary application of the WBAN (for example, three-axis accelerometers), each WWSN has been fitted with a Bosch BMP085 AAPS for localization and limb position tracking. This small, low-cost, low-power device can detect air pressure differences of \(<3 \text{ Pa} \) in ultrahigh resolution mode, translating to approximately 25 cm in altitude change, and advertises \(<1 \text{ Pa} \) resolution with software averaging. The AAPS draws 12 \( \mu \text{A} \) at 1.8–3.6 V if sampled at 1 Hz at 25 °C; assuming an upper bound case where 10 Hz sampling translates to a \( 10 \times \) power consumption, each AAPS would consume about 0.43 mW. This would only minimally tax a typical CR2032 WWSN battery, which provides 675 mWh. We note that MEMS sensor technology evolves very rapidly, and the precision of the AAPS is the key factor in determining the minimum confidently detected WWSN spacing.

To determine WWSN placement through height inference, each node transmits air pressure \( P \) and temperature \( T \) readings together with data collected for the WBAN’s primary application to the base station. In our setup, a personal computer aggregates all sensor data and performs postprocessing using MATLAB. Although pressure readings can be compared directly for WWSN localization purposes, altitudes \( h \) at each node location can also be deduced using (1) from \( p \) by obtaining \( p_0 \) from an external source; in our setup, we opted to use Environment Canada’s weather report.

B. Localization Technique Validation and Results

The experimental validation of our technique consists of the following major procedures to evaluate the system’s performance in detecting the changes in height required for WWSN localization and limb position tracking.

1) Selecting appropriate AAPS sampling parameters (one sensor, one position).

\(^1\)Sea-level standard temperature \( T_0 \), earth-surface gravitational acceleration \( g \), dry air molar mass \( M \), universal gas constant \( R \), temperature lapse rate \( L \).
2) Ensuring that the selected AAPS can accurately and reliably detect small-scale changes in air pressure, applicable along the height of a human body (one sensor, two positions).

3) Examining and correcting for intrinsic differences between two different AAPSs, to ensure that readings from one can be compared with readings from another (two sensors, one position).

4) Combining the previous procedures to enable the WBAN to measure the air pressure at two limb locations without reusing the same sensor (two sensors, two positions).

While data were manually captured at controlled times for the purpose of validating our experiment, we expect a commercial-grade WBAN to continuously sample the AAPS and utilize a rolling window to repeatedly perform the statistical testing described in this section to monitor the position of WWSNs in the WBAN.

C. Selecting Appropriate Pressure Sensor Sampling Parameters (One Sensor, One Position)

The proposed system aims to expedite the process of accurately verifying WWSN placement while reducing power consumption. On one hand, the accuracy of the verification process depends on the raw AAPS readings output, whose error margins (noise), in turn, depend on the sampling rate. Empirical results obtained through our WBAN setup reveal that by employing the highest resolution mode of the AAPS, a 10-Hz sampling rate suffices to minimize noise and reduce power consumption by not overloading the microprocessor unit (MCU) through oversampling. However, a suitable sampling time window must be obtained in order to optimize the accuracy of the WWSN placement verification assessment.

To this effect, we placed one node on a stationary surface and sampled the AAPS readings for one hour. Simple visual inspection and comparison with Environment Canada weather reports corroborated either steady air pressure variations (increasing or decreasing) or a stable output, depending on the current weather conditions. However, our approach is not impacted by this, because the time scale of the WWSN placement verification process is too short compared to the length of time it takes for atmospheric air pressure changes to have any effect on the system’s accuracy. It follows that a placement verification process subject to rapid, artificial changes in atmospheric air pressure is prone to inaccuracies because this circumstance skews the probability distribution function (PDF) of the readings’ error margin. In other words, the proposed scheme enhances location verification reliability by ensuring that the statistical analysis is performed over data samples unambiguously described by a probability distribution, as detailed shortly.

By taking 1 h of pressure data readings where the sea level air pressure remained stable, and by examining window sizes (subsets of this data) between 1 and 60 s, the mean and spread of pressure readings remained very similar throughout this range, as depicted in Table I. By characterizing the PDF and cumulative distribution function (CDF) of the data samples at hand, we can define CIs that can be referenced to determine pertinent data sampling windows that maximize the accuracy of the system’s assessment process. We examine the goodness of fit (GOF) of the data from each window size against a Gaussian distribution with 95% CI. Fitting the data to common distributions using GOF tests showed that a Gaussian distribution had the best fit. From Table I and the probability plot in Fig. 3, we can see that sampling windows of 2, 3, 5, and 10 s produced readings that could be confidently approximated by a Gaussian distribution, that is, their p-values were > 0.05. Furthermore,

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the 3-s sampling window returned the highest \(p\)-value, meaning this sampling window would be most preferable, in order to ensure that the error estimation process corresponds with a Gaussian PDF describing the actual data samples output by the sensor. Otherwise, employing an error estimation scheme for a data stream with mismatching PDF would invalidate the accuracy of our approach. Repeating this analysis with two more sets of pressure data also produced the same findings, where the 3-s sampling window gave the highest \(p\)-value.

The different sampling window trials shown in Table I and the corresponding pressure reading distributions gives us a good reference point to determine the length of the sampling window based on the GOF results. With too short of a sampling window, too few data points are available for an accurate fit. However, if we take measurements for too long, overall fluctuations in atmospheric air pressure due to the weather would skew our readings, thus limiting the accuracy of our proposed approach.

### D. Verifying Assessments of Height Measurements

(One Sensor, Two Positions)

In this section, we describe the verification process to ensure that our hardware can accurately and reliably detect the small-scale changes in air pressure representative of heights along the human body, in accordance with the results obtained and described in Section III-C. This is achieved by placing one AAPS at two locations spanning a controlled vertical distance apart, and by ensuring that the pressure measurements at the two locations can be distinguished from one another if the obtained measurements statistically remain within the CI. Here, we first utilize only one AAPS to negate the intrinsic hardware differences between two different sensors. We demonstrated this technique and reported preliminary results in [1]. In a practical WBAN, we need two WWSNs to obtain measurements at two positions, as described and examined in the next sections. We placed the single sensor at two baseline heights, defined as 0 cm (position I), and at 60 cm above position I (position II) and obtained pressure data at the two positions. The 60 cm height difference was selected as a starting point indicative of the typical minimum distance between two limb positions we expect our system to monitor, based on a two-WWSN WBAN with one arm node and one leg node. We examine 3-s data portions using two-sample T-tests. Since identical sensors were used, we assume equal variances between the two sets of data. First, we compare one set of sample data from position I against a set from position II, and repeat the test ensure reproducibility. Next, we compare sample data taken from the same position against each other to ensure that same position data are not falsely detected as being different. A small \(p\)-value enables us to reject the null hypothesis; that is, there is a statistically significant difference in height estimates at the two positions.

From Table II, we can see that for all three trials, placing the sensor at 60 cm altitude differences returned pressure difference measurements of on average 8–10 Pa, with an estimated difference of 7–12 Pa with a 95% CI. Furthermore, the two-sample T-tests returned \(p\)-values of 0 for all three trials, confirming that the height estimate at position I is statistically different from that at position II with \(>99.9\%\) CI. This means that the sensor readings from location 1 differ enough from location 2 to enable the system to detect the changes in air pressure, and thus height, that we require. From Table III, comparing pressure data taken from the same positions against each other, the two-sample T-tests for all three trials returned \(p\)-values \(>0\). This means, as expected, that the results are insufficient to falsely identify different height assessments given the same position. Repeating this experiment with more data provided agreeable results; further trials, including data collected on different days and at different physical locations, all corroborated \(p\)-values of 0 in Table III, supporting that data from the two positions are statistically distinguishable.

### E. Verifying Assessments of Height Measurements

(Two Sensors, One Position)

In this section, we describe the process of verifying that two different sensors measure the same pressure when placed in the same position. During initial experimentation, we discovered that AAPSs placed together at the same altitude reported...
pressure readings offset from one another. Moving both AAPSs the same distances vertically produced the same offsets. This showed a constant offset and implied that the differences in response between otherwise identical AAPSs were due to insufficient precision in the eleven 16-bit factory calibration coefficients that are unique to each sensor, possibly because the sensor was designed for measuring more macroscale air pressure readings. This realization highlights the importance of understanding the operation of AAPSs for measuring fine-grain, human-scale height differences at the highest possible resolution. After more testing with a third AAPS, comparable constant offset observations were made. These offsets relative to each sensor were found to not change over time. Thus, this one-time constant offset correction calibration process is important in enabling meaningful comparisons of readings between different AAPSs, and thus a reliable height-based WWSN placement estimation system.

To substantiate this claim, we place two AAPS-equipped WWSNs side-by-side (at the same altitude) and examine the mean and spread of the pressure data from each node. Using the 3-s, 10-Hz sample window determined previously, we can see in Table IV that applying a two-sample T-test (assuming equal variances) returned differences in measurements between two AAPSs placed at the same position of on average 40–43 Pa, with an estimated difference of 37–45 Pa with a 95% CI. Clearly, without offset correction, any comparisons made between different sensor hardware are prone to error, as the offset is approximately four times larger than the change in pressure we saw over a 60-cm vertical distance. To ensure that we can apply this correction factor just once and be able to meaningfully compare pressure readings between different hardware, we ensure that this offset is indeed a constant offset, that is, the offset does not change with altitude or over time. This was accomplished by repeating the experiment at different altitudes over the height of a typical human body, and examining the pressure offset between the two sensors. Measurements obtained between two nodes at the same location revealed very similar estimates, and that the offset for our two particular AAPSs remained at approximately 40 Pa. This confirms that the offset can be treated as being constant for the purposes of our approach, thereby enabling us to compare pressure measurements between sensors so long as this offset is accounted for.

F. Validating Assessments of Height Measurements in a WBAN (Two Sensors, Two Positions)

In this last step, we combined our previous approaches to estimate air pressure measurements at two different locations. Because verifying the correct placement of WWSNs on limbs requires the ability to measure the air pressure at each location simultaneously, we must validate that using two sensors to measure pressures at two locations produces data comparable to those described in Section III-D, where the output of a single sensor was gauged at two positions (one case at a time). Again, we utilize a 3-s sampling window as per the results presented in Section III-C.

Using the same two-sample T-test and assuming equal variances as per the procedure in Section III-D, as well as constant offset as per Section III-E, the results displayed in Table V show that the pressure differences between the two positions are indeed statistically significant, and the test verifies that the two positions are indeed different. Also, the 7–15-Pa estimate for the pressure difference at a 95% CI is very comparable to the 7–12-Pa estimate for the pressure difference with 95% CI at 60 cm apart observed in Section III-D; see Table II. Performing more trials produced similar pressure difference estimates. Thus, the test demonstrated that the constant offset correction is successful, and valid comparisons can be made between pressure measurements from two nodes. Empirical CDF plots for each of the three trials show the measured pressure differences between the two nodes at the two positions (60 cm apart).

By determining and accounting for the differences in sensor hardware in a one-time calibration process, where the AAPSs are placed at the same vertical location, to correct the constant

<table>
<thead>
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<th>Position</th>
<th>N</th>
<th>Mean</th>
<th>SDev</th>
<th>SE Mean</th>
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</thead>
<tbody>
<tr>
<td>1 @0cm</td>
<td>30</td>
<td>101913.87</td>
<td>2.80</td>
<td>0.51</td>
</tr>
<tr>
<td>1 @0cm</td>
<td>30</td>
<td>101911.80</td>
<td>2.54</td>
<td>0.46</td>
</tr>
<tr>
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<td>T-Value = 2.99 P-Value = 0.004 DF = 58</td>
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<th>Mean</th>
<th>SDev</th>
<th>SE Mean</th>
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</thead>
<tbody>
<tr>
<td>1 @0cm</td>
<td>30</td>
<td>101913.87</td>
<td>2.80</td>
<td>0.51</td>
</tr>
<tr>
<td>1 @0cm</td>
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<td>101911.80</td>
<td>2.54</td>
<td>0.46</td>
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<th>Mean</th>
<th>SDev</th>
<th>SE Mean</th>
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<tr>
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<td>30</td>
<td>101911.80</td>
<td>2.54</td>
<td>0.46</td>
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<tr>
<td>1 @0cm</td>
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<td>101913.70</td>
<td>2.83</td>
<td>0.52</td>
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<td>Estimate for difference μ(0cm) - μ(0cm):</td>
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<td>95% CI for difference:</td>
<td>(-3.289, -0.511)</td>
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<tbody>
<tr>
<td>N1</td>
<td>30</td>
<td>101956.33</td>
<td>4.72</td>
<td>0.86</td>
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<td>N2</td>
<td>30</td>
<td>101913.87</td>
<td>2.80</td>
<td>0.51</td>
</tr>
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<td>Estimate for difference μ(N2) - μ(N1):</td>
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<td></td>
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<tr>
<td>95% CI for difference:</td>
<td>(40.46, 44.47)</td>
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<tr>
<td>T-Test of difference = 0 (vs not ==):</td>
<td>T-Value = 42.37 P-Value = 0.000 DF = 58</td>
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</tr>
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<td>N2</td>
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<td>101911.80</td>
<td>2.54</td>
<td>0.46</td>
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<td>(40.13, 44.27)</td>
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<td>T-Test of difference = 0 (vs not ==):</td>
<td>T-Value = 40.80 P-Value = 0.000 DF = 58</td>
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<tbody>
<tr>
<td>N1</td>
<td>30</td>
<td>101953.77</td>
<td>5.68</td>
<td>1.00</td>
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<td>N2</td>
<td>30</td>
<td>101913.70</td>
<td>2.83</td>
<td>0.52</td>
</tr>
<tr>
<td>Estimate for difference μ(N2) - μ(N1):</td>
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<tr>
<td>95% CI for difference:</td>
<td>(37.75, 42.39)</td>
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<tr>
<td>T-Test of difference = 0 (vs not ==):</td>
<td>T-Value = 34.58 P-Value = 0.000 DF = 58</td>
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TABLE V
COMPARING THE MEASURED PRESSURES DISTRIBUTION WITH TWO SENSORS AT TWO POSITIONS WITH CONSTANT OFFSET CORRECTION, USING A TWO-SAMPLE T-TEST

<table>
<thead>
<tr>
<th>Node / Position</th>
<th>N [#]</th>
<th>Mean [Pa]</th>
<th>StDev [Pa]</th>
<th>SE Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trial 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N1 @0cm</td>
<td>30</td>
<td>101936.33</td>
<td>4.72</td>
<td>0.86</td>
</tr>
<tr>
<td>NC @60cm</td>
<td>30</td>
<td>101905.47</td>
<td>3.90</td>
<td>0.71</td>
</tr>
<tr>
<td>Estimate for difference μ(N2) - μ(N1): 12.87</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>95% CI for difference: (10.63, 15.11)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>T-Test of difference = 0 (vs not =):</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>T-Value = 11.50 P-Value = 0.000 DF = 58</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Trial 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N1 @0cm</td>
<td>30</td>
<td>101914.00</td>
<td>5.07</td>
<td>0.92</td>
</tr>
<tr>
<td>NC @60cm</td>
<td>30</td>
<td>101905.07</td>
<td>3.98</td>
<td>0.73</td>
</tr>
<tr>
<td>Estimate for difference μ(N2) - μ(N1): 10.93</td>
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<tr>
<td>95% CI for difference: (8.58, 13.29)</td>
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<td></td>
</tr>
<tr>
<td>T-Test of difference = 0 (vs not =):</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Value = 9.29 P-Value = 0.000 DF = 58</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trial 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N1 @0cm</td>
<td>30</td>
<td>101913.77</td>
<td>5.68</td>
<td>1.00</td>
</tr>
<tr>
<td>NC @60cm</td>
<td>30</td>
<td>101903.60</td>
<td>2.92</td>
<td>0.53</td>
</tr>
<tr>
<td>Estimate for difference μ(N2)-μ(N1): 10.17</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>95% CI for difference: (7.83, 12.50)</td>
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<tr>
<td>T-Test of difference = 0 (vs not =):</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>T-Value = 8.72 P-Value = 0.000 DF = 58</td>
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</table>

offset analyzed in Section III-E, the same pressures are measured by the two separate WWSNs when placed at the same altitude. Thus, it is possible to draw accurate and meaningful comparisons between the air pressure measurements at each limb, thereby enabling the WBAN to pinpoint its WWSNs.

G. Localization Technique Discussion and Limitations

By examining altitude differences between WWSNs, we have introduced and demonstrated a new scheme for WWSN localization, by leveraging fine-grain hypsometric information of the Earth’s atmosphere. Given the physical topology of the WBAN, the scheme confidently identified which node was attached to which limb based on the altitude information of each WWSN. The placements at each height corresponded to placing WWSNs on the head, arm, and/or leg. This scheme assumes the WWSN placement discovery, and verification process takes place while the patient is upright to maximize the distances between the nodes, and thus improve detection accuracy. We anticipate that this will not limit the real-life usefulness of this system; as discussed in Section III, node localization for limb recognition and tracking is only required each time the patient takes off and replaces the WWSNs from his or her body. In our experiment, we tested WWSNs at 60 cm apart, indicative of the minimum expected distance between a patient’s arm/wrist and lower leg. The larger the distance apart, the higher the accuracy of the system. Since beginning our study, Bosch has released the BMP180 AAPS to replace the BMP085 AAPS we utilized in this study, which increases detection accuracy from 3 Pa (25 cm air column) to 2 Pa (17 cm air column) in ultrahigh resolution mode, at comparable size and cost. Prior to selecting the BMP085 AAPS, we wished to perform this study with the VTI SCP1000 AAPS which advertises a 9 Pa detection accuracy. However, this AAPS was discontinued in the months before our study began.

In contrast to traditional WWSN localization techniques surveyed in Section II, our approach does not rely on having a large number of nodes to perform localization, nor stationary beacon nodes to perform ranging. One limitation of the approach is its inability to distinguish between different nodes attached at the same height on the body, for example, a WWSN attached to the left arm and another attached to the right arm. An additional technique would be required to identify left and right nodes. Notwithstanding this, since the human body is slender, and more WWSNs are typically distributed along the height of a body, by being able to self-identify WWSNs at different heights, we have reduced the number of nodes requiring manual identification to “left” and “right” nodes, which is far more convenient for the patient.

IV. ENHANCING ACCELEROMETER-BASED FALL DETECTION SCHEMES WITH LIMB POSITION TRACKING

A. Overview of Fall Detection Experimental Setup

In a typical on-body fall detection system, accelerometers are fitted in WWSNs to capture x-, y-, and z-axis limb acceleration, and elementary fall detection techniques look for “falls” by monitoring acceleration magnitude peaks due to impact [12], [13], [15], [16]. However, as explained in Section II, motion from certain daily activities such as sitting down on a chair often produces large z-direction acceleration spikes and could be mistaken as a “fall” [13]. Since traditional on-body schemes lack contextual awareness, the expected detection accuracy based on impact magnitudes alone cannot be entrusted for remote long-term at-home fall monitoring.

In this section, we apply our WWSN placement recognition technique to improve such an on-body fall-detection WBAN. Such systems typically comprise of one or two WWSNs placed on a patient’s body for long-term monitoring, which makes our localization scheme in Section III a good candidate for providing enhanced contextual awareness. We introduce limb position awareness to monitor the patient’s body movements in time intervals surrounding any detected impact. With our enhancement, a WBAN continuously tracks and monitors the instantaneous air pressure at each limb to deduce the patient’s physical state, immediately after significant accelerometer activity is detected that could indicate a “fall-like” event. By comparing pressure differences against the known WWSN placement topology, the WBAN can examine the position of the arm relative to the leg, and deduce if the user is upright (standing or sitting up, where the nodes are at different vertical positions), or lying down (where the nodes are vertically at the same position). With this contextual information, we expect to be able to reduce false-positive detections (see Section IV-B), where falls were detected but no fall had occurred. To demonstrate that this scheme is beneficial to an on-body fall detection system, we scope our study to replicate the variety of typical daily at-home activities the user being monitored is expected to encounter, to observe how our proposed enhancement responds in determining the patient’s context, compared to a system relying solely on accelerometer impact response. Specifically, the tasks studied and replicated in Section IV-C include walking, traversing stairs, sitting down, lying down, and a fall to the ground. The change in acceleration and air pressure at each WWSN is recorded and examined.
The WBAN and experimental configuration in Section III, consisting of one WWSN attached to the arm, and another attached to the leg (see Fig. 1), was reused. This is to demonstrate that a Parkinson’s disease limb tremor monitoring system, such as [2], could be easily upgraded with fall-detection capabilities, without additional WWSNs or moving nodes around. For a pure fall-detection WBAN disregarding primary application sensor placement, it is worth noting that studies on sensor placement to record acceleration due to falls has so far been inconclusive [18]; some have suggested behind the ear [12], the trunk [13], or the head and waist [15] areas as being the optimum locations for a fall sensor. Our proposed approach aims to increase the sensitivity and performance of on-body fall detection and allow the primary application of the WBAN to dictate the placement of WWSNs.

B. Fall Detection Hypothesis Testing

We define the following fall detection hypotheses.

1) $H_0$ (null hypothesis)—A fall was detected (the two WWSNs are found to be at the same vertical position).

2) $H_1$ (alternative hypothesis)—No fall was detected (the two WWSNs are not found to be at the same vertical position).

These hypotheses aid in describing the four possible outcomes.

1) A fall was detected, and there has indeed been a fall (true-positive, desired outcome, accept $H_0$).
2) A fall was detected, but there was no fall (false-positive, undesired outcome, Type I error from falsely rejecting null hypothesis).
3) A fall was not detected, and there had indeed been no fall (true-negative, desired outcome, reject $H_0$ correctly).
4) No fall was detected, but there was a fall (false-negative, Type II error from falsely not rejecting null hypothesis).

The hypotheses are formed in this order to ensure that the system only concludes that no fall has occurred if it can confidently be sure that the null hypothesis can be rejected. This is because an undetected fall (a false-negative) has more fatal consequences than one where no fall has occurred but an alarm is triggered (a false-positive).

We further define the probability that the patient requires assistance and caregiver attention based on $P(H_0)$ as the intersection of $P(\text{fall})$, the probability that an impact or free-fall has occurred as detected by an accelerometer, and $P(\text{lyingdown})$, the probability that the patient is lying down, as detected by AAPSs, in the time immediately following:

$$P(H_0) = P(\text{fall}) \cap P(\text{lyingdown}).$$

In a nutshell, our proposed fall detection enhancement considers both $P(\text{fall})$ and $P(\text{lyingdown})$, as opposed to traditional on-body systems that rely solely on $P(\text{fall})$. The WBAN is to make an assessment based on the occurrence of AAPSs at the arm and leg reporting similar altitude to estimate $P(\text{lyingdown})$ (implying that the patient is lying down) within a margin of error, given that an accelerometer has indicated a fall event based on the magnitude of impact or free-fall $P(\text{fall})$. Falls requiring attention based on $P(\text{fall})$ alone have been previously studied in detail in [12], [13], [15], and [16]. Thus, this section will focus on the performance of the $P(\text{lyingdown})$ enhancement, and whether or not the enhancement can accurately and reliably detect that a patient is lying down as a result of the daily at-home activities studied. We quantify our system’s performance in detecting a patient as “lying down” by sampling 3-s windows of pressure data immediately after the accelerometer observes spikes from the replicated scenario, and performing two-sample T-tests between the two WWSNs for each data set (trial). Depending on the scenario, the $p$-value should either conclude that the two nodes are at different altitudes (the patient is not lying down), or that the nodes are not at different altitudes, inferring that the patient is lying down. The closer the $p$-value is to 0, the more confident we can be that the patient is not lying down.

C. Fall Detection Enhancement Experimental Results

1) Scenario 1 (Walking): In a fall detection system, aside from staying still, walking is likely the most elementary and common movement type. Our subject replicates typical walking on level ground, representative of ordinary daily activities around the home. As shown in Fig. 6,2 each footstep results in an acceleration spike 0.5–2 g in magnitude. The two-sample T-tests (see Table VI) estimated a 7–14 Pa difference in pressure.
between the two positions, with a p-value of 0, indicating with 100% certainty a true-negative case, that null hypothesis can be rejected and that the arm and leg nodes are indeed at different vertical positions. Thus, we can deduce from this information that the patient is upright (from the AAPS data) and moving about (from the accelerometer data) and has not suffered a fall.

2) Scenario 2 (Walking Up/Down Stairs): The walking scenario was also studied on a staircase, to recognize that falls while walking are also likely while traversing stairs [30]. Scenario 2A describes the walk up, and Scenario 2B describes the walk down. Performing two-sample T-tests (see Table VI) gave a 4–15 Pa estimated difference in pressure between the two positions, with a p-value of 0 for both scenarios, once again indicating a true-negative case, that the arm and leg are at different vertical positions, with absolute certainty. The results also infer that the arm and leg are closer together compared to Scenario 1, which is valid because of the leg motion involved in climbing stairs. As an aside, while the accelerometer sees similar motion data in both walking scenarios, the difference due to walking up and down a flight of stairs is clearly observed in Fig. 7, further aiding in the contextual awareness and determining the patient’s motion pattern.

3) Scenario 3 (Sitting Down): In this scenario, we analyze the response of the system due to sitting down onto a chair, and standing up. Fig. 8 shows the data acquired from our test subject repeatedly sitting down and standing up. Impact between the subject and the chair is clearly distinguishable in the accelerometer data, which would be used to trigger the location measurements. Two-sample T-tests (see Table VI) estimate a 8–16 Pa difference in pressure between the arm and leg positions, with a p-value of 0 for both scenarios, again indicating with very high confidence that we can reject the null hypothesis as desired, as the user is not lying down. As well, from the pressure and inferred altitude, we can differentiate between periods when the user is standing up and sitting down as well, since the distance between the arm and leg nodes narrows significantly when the user sits down.
Fig. 9. Scenario 4: Lying Down—Arm and leg acceleration, air pressure, inferred altitude. The period in which the test subject was lying down can clearly be seen by the overlapping arm and leg node AAPS readings. This overlap suggests that the two nodes are vertically at the same height.

4) Scenario 4 (Lying Down): This scenario involves lying down onto a bed from an upright position. The accelerometer trace in Fig. 9 illustrates the fall. Examining the pressure data during the period the user is lying down (when the AAPSs from the two WWSNs become placed at the same altitude), we observe a fast response as the two traces converge to the same pressure and altitude readings between 7 and 15 s. Two-sample T-tests in this region estimate a 0–5 Pa difference in pressure between the arm and leg positions with 95% CI (see Table VI), and p-values >0 demonstrate that, as expected, we cannot from this data statistically reject the null hypothesis (that the arm and leg are at different heights, that there was no fall). Similar to Scenario 4, this would imply a possibility of the patient lying down. This is consistent with a visual examination of Fig. 9, where the arm and leg node pressure traces clearly converge. Since the WBAN is no longer confident that the patient is still upright, in considering both P(fall) and P(lying down), if an accelerometer-detected “fall” preceded this change in arm and leg position, a caregiver can be immediately alerted of a potential situation. A closer examination of both acceleration magnitude and air pressure convergence shows strong a similarity to the data obtained by lying down in Scenario 4.

D. Fall Detection Enhancement Discussion and Limitations

This enhancement demonstrated reliable detection of a wearer’s state during the different at-home activities replicated, for deducing P(lying down) in reducing false-positive detections. From our results, the WBAN successfully differentiated between an upright position and lying down. While the AAPSs alone were unable to further distinguish between specific different upright positions (standing versus sitting), we observe that the usefulness of a contextually aware WBAN is highlighted in a fall detection application; a much better decision on the
patient’s condition can be made simply by knowing if a patient is lying down. As explained, in some of these scenarios, relying solely on accelerometer data would make it difficult to distinguish between a “slow fall” and other fall-like activity, as in [24]. Moreover, it has been identified that many elderly people “fall” onto a chair when sitting down due to reduced muscle strength with old age [13]. This results in higher acceleration peaks than analyzing young adults sitting down, who have much greater control over the speed of their body motions; depending on how the patient sits on a chair, the acceleration profile could be similar to an actual fall. With our proposed enhancement, by considering both the $P(\text{fall})$ explored extensively in previous works and $P(\text{lyingdown})$, augmenting arm and leg position information clearly shows that after such a “fall” on a chair, the WBAN can now be aware that the patient is still upright and not lying on the ground, thus reducing false-positive estimates of $P(H_0)$ when compared to previously studied on-body fall detection systems where $P(H_0)$ was solely deduced by $P(\text{fall})$.

We can foresee some cases where augmenting limb position information would not help reduce the probability of false-positive detection. From our experimental data, we found it difficult to distinguish activities for a patient lying down and falling using either accelerometer data or altitude information. Both the lying down scenario and emulated fall produced similar accelerometer peaks; comparing the accelerometer data from the arm node at time 4–6 s in Figs. 9 and 10 with [13, Fig. 1A], both cases generate accelerometer responses that would indicate a fall, although lying down on a bed is not actually a fall. While beyond this specific case, our scheme has demonstrated improvement in false-positive detection, to further improve our proposed enhancement, we could extend the scope of our study to the fine-tuning of T-test parameters, for example, the acceptable $p$-value threshold at 95% CI to determine if the nodes are at different positions. We could also further examine the instantaneous impact acceleration characteristics, or expand on the types of contextual information provided to the WBAN, for example, by incorporating additional sensors such as heart rate to even better distinguish between body states.

V. CONCLUSION

We have presented and experimentally verified a new approach to determine the location of WWSNs mounted along the height of a patient’s body by measuring and comparing instantaneous air pressures at each node. The spatial information enables the WBAN to automatically identify and map which WWSN is mounted on which limb. We believe this technique is novel because the technique reliably maps a wearer’s limb locations in absolute coordinates longitudinally along the length of the body, without requiring additional nodes or off-body infrastructure. We have experimentally verified the feasibility and practicality of implementing this approach into an existing WBAN designed for long-term at-home patient monitoring in Section III. We have shown that commercially available AAPSs can be utilized to produce reliable and accurate position information. Once the WWSNs are identified, by continuously tracking the limb positions, the WBAN is able to infer basic daily activities, for example, standing and lying down. While a 60 cm separation between two WWSNs, indicative of a patient’s arm and leg limb spacing, was studied, the scheme’s granularity is limited only by the accuracy and precision of the AAPS hardware (see Section III-G). In adapting the localization scheme to an autonomous commercial WBAN with minimal patient intervention, some challenges could include power consumption optimizations (such as adaptive sampling frequency) toward long-term monitoring, and the detection of whether or not WWSNs are currently being worn or their physical placements have changed (see Section III-A).

This scheme enhances the context awareness of WBAN applications such as fall-detection systems, to better preclude falls requiring attention from other “fall-like” activities where the patient is clearly still standing (see Section IV). Augmenting limb position information has enabled our on-body fall detection WBAN to better deduce and classify activities that accelerometer-only systems traditionally detect ambiguously or with a high degree of false-positives (Type I errors). By enabling the WBAN to continuously track the patient’s limb positions, on-body fall detection systems can consider both $P(\text{fall})$ and $P(\text{lyingdown})$ to make more informed decisions on $P(H_0)$ and reduce false-positive detections.

As hardware continues to evolve and higher performance sensors are developed, this scheme shall benefit from more precise pressure data, but in the meantime, filters could be employed to reduce noise, as long as no significant MCU overhead is introduced, producing a further tradeoff between power consumption and speed. Since the AAPSs simply add an extra stream of pressure data at each WWSN, transmitted easily over IEEE 802.15.4 in our prototype WBAN platform, we do not anticipate wireless channel limitations when adapting the system to Bluetooth, Bluetooth Low-Energy, or other WBAN protocols. This scheme could even be extended to traditional WSNs (see Section II) to explore collaborative localization with different sensors and radio signal-based area and distance-measuring localization schemes.

Overall, we believe this new technique has a strong promise in delivering accurate and reliable WWSN localization and limb recognition and monitoring to the m-health field.

REFERENCES


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