# Vertical Hand Position Estimation with Wearable Differential Barometery Supported by RFID Synchronization

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**Abstract.** We demonstrate how a combination of a wrist-worn and stationary barometer can be used to track the vertical position of the user's Hand with an accuracy in the range of 30 cm. To this end, the two barometers synchronized each time an RFID reader detects them being in proximity of each other. The accuracy is sufficient to detect a specific shelve of a cupboard on which something has been placed or determine if the user's hand is touching his/her head or the torso. The advantage of the method over IMU based approaches is that it requires only a wrist-worn sensor (as could be implemented in a smartwatch) and a reference either in an often access location in the environment or a pocket (e.g.in the smartphone) and it does not depend on a stable magnetic environment. The proposed system was tested in two different activities: Shelve recognition in a warehouse picking scenario and movement of the arm to specific body locations. Despite the simplicity of our method, it shows initial results between 55–62% and 73–91% accuracy, respectively.

**Keywords:** Relative pressure · Barometer · RFID · Order picking · Wearable sensing

## 1 Introduction and Related Work

Our hands are the primary means of interacting with our physical environment. Thus, the position of user's hands is a crucial piece of information for a broad range of context recognition task. It is made difficult by two considerations. First, in many cases, to be meaningful, the tracking has to be accurate to within 10–50cm. This is, for example, the case when we need to know which object the user has picked from a shelve, which/how she/he has interacted with a household device, or when he/she has taken a piece of food into the mouth. Second, for

The research reported in this paper has been partially supported by the BMBF (German Federal Ministry of Education and Research) in the project HeadSense(project number 01IW18001). The support is gratefully acknowledged.


L. Mucchi et al. (Eds.): BODYNETS 2019, LNICST 297, pp. 24–33, 2019.
https://doi.org/10.1007/978-3-030-34833-5_3

many applications, the amount of instrumentation that can be introduced into the environment to facilitate the tracking is limited. In an ideal case, the tracking would be achieved by a sensor that can be easily integrated within a smartwatch or a fitness tracker with no need for further environment instrumentation.

Currently, there are three main approaches to hand tracking. First, are classical object tracking systems. These are either expensive and requiring elaborate infrastructure (such as visual tracking [2], UWB, ultrasound [8]), or have problems achieving the needed accuracy (e.g., Bluetooth [6] or WiFi). Second is the use of RFID tags in the environment combined with a wrist-worn RFID reader (see e.g., [5] as an example of the use of RFID based object interaction detection for activity recognition). The disadvantage is the need to mark every relevant object with an RFID. Also, given the size of the antenna that can be fixed at the wrist there can be problems with the detection of some interactions where the wrist does not approach the tag close enough in the usual interaction mode of the specific object (e.g. tag fixed to the bottom of a cup and the used grabbing the cup by the handle). Finally, IMUs can be used together with appropriate bio-mechanical body models to track the exact position and orientation of the wrist. However, given the degrees of freedom of human joints, this can not be achieved by a wrist-worn sensor alone but requires at least three sensors: one at the wrist, one at the upper arm and one at the torso (at least for an exact solution), under a stable magnetic environment.

This paper focuses on a subset of the hand tracking problem: the detection of the vertical position of the wrist. Specific applications that we consider is detecting which shelve from a cupboard the user has reached to (relevant for household activity monitoring and order picking industrial environments) and the detection of gestures such as reaching to the head/mouth (relevant for example for nutrition tracking). To this end, we propose to use a wrist-worn digital barometer. Such devices are already widely used in smartphones and finding their way into smartwatches. The use of digital barometers has been widely studied in the context of indoor navigation [4]. The idea is that while the absolute air pressure varies too much due to weather conditions to be useful for indoor level estimation, short term changes in the air pressure are a reliable indication of going up or down. Within the accuracy needed to detect going up or down one level in a building drift and other sources of errors [9] have been shown to be manageable. Short term change in air pressure has even been used to distinguish sitting and standing [11] and for fall detection [3].

For the applications envisioned by our work, such as the detection of a specific shelve accessed by the user, such approaches are not directly applicable for two reasons. First, we need to detect not just change in elevation but must somehow translate the measurement to absolute elevation. Second, the envisioned precision of around 30 cm is influenced not just by natural air pressure variations but also by the drift of typical, low-cost sensors. Our solution is based on the observation that in most environments, there is a fixed location with known elevation, which the user's hand frequently approaches. Thus, for example, the hand will often "hang" around the hip. In warehouse picking applications, the user has a pushcart on which items are placed after being taken from the shelves. Such locations can be used to place a reference barometer and an RFID reader while adding an RFID-Tag to the barometer at the user's wrist. Each time the user's hand approaches the location, it is detected by the RFID reader, and the readings of the stationary and the wrist-worn barometer are synchronized. The elevation of the wrist is then tracked by comparing the signal of the wrist-worn barometer to the reference.

In this paper, we describe the implementation of a system based on those ideas and the quantitative evaluation of its performance demonstrating, that given the drift and accuracy of typical low-cost sensors it is indeed a feasible approach.

## 2 System Description

The prototyping platform used is a combination between the development board STM32L475 DISCOVERY with Arm Cortex-M4, BMP388 Bosch pressure sensor, the RFID PN532 chip, and a firmware development based in MBED OS 5.12. Furthermore, the system is complemented with a fast and straightforward vertical position model using the barometer pressure measurements and RFID detection to signal the reference position. The communication to the sensors is based on I2C port at 400KHz. The data from the platform was obtain using ST-LINK-UART at a baud-rate 1 Mbps. As the firmware is based on a real-time operating system (MBED-OS 5.12), the timing is not sequential, and it depends on the schedule and the total preemptive RTOS. The data of the pressure has a sampling-rate below 62,5 Hz (16 ms) 90% of the time, as shown in Fig. 2, suitable for detecting a picking action(around 1 s). The hardware depicted in Fig. 1 and two systems were built, one of those, used as a reference with the RFID-Reader and the other one assembled on the wrist with RFID-TAG.

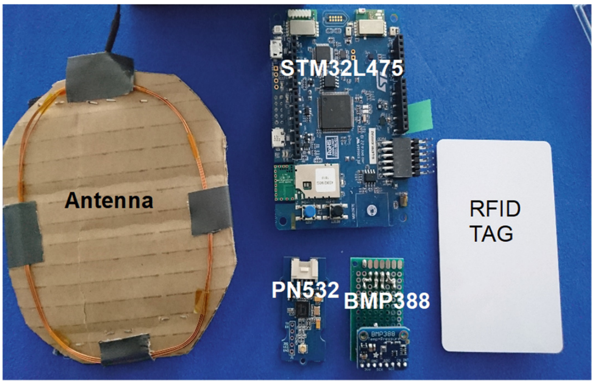


**Fig. 1.** Hardware: Antenna, STM32L475, PN532(RFID Reader), BMP388, RFID TAG

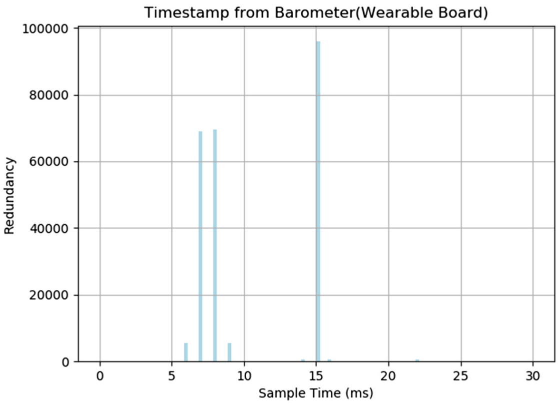


**Fig. 2.** Sample rate distribution for the pressure

## 2.1 Vertical Position Model

The vertical position model is based on the well known, and highly used relationship between the barometric pressure and the height as in [4,7,12] which is expressed in the following formula 1.

$$H = \frac{Temperature}{Beta} \cdot \left[\frac{Pressure}{PressureRef}^{\frac{-Beta*R}{g}} - 1\right] \tag{1}$$

In [12], they used a base barometer and a rover barometer and made the height estimation relative to the sea level pressure. Since the air pressure varies typically between 950 and 1050 hPa during a year, the expected variation in sea level due to air pressure is between +63 cm and –37 cm around mean sea level, which is a situation that we cannot quantify or control. In [9] they studied the sources of errors in the barometer pressure measurements, and they concluded that barometers in differential mode would provide highly accurate altitude solution, but local disturbances in pressure need to be taken into account in the application design. We proposed to apply the formula 1 but, relative to a reference point pressure and a wearable pressure device, removing the sea level pressure dependency entirely, and having access to monitor the changes in the reference height. In the case of temperature on the reference level, the authors in [7] used the temperature as an average of standard atmospheric pressure and current atmospheric pressure, in our case the temperature is considered as the average value between the reference-point and the wearable-device-temperature.

To implement this approach, in the first step two devices equally equipped as described before were placed on the same table (same height) close to each other, and the pressure values were recorded in 3 different days for 20–45 min as depicted in Fig. 3, these recordings were done indoor without interruptions (windows and door closed), this test was done to obtain the static information of the system.The two pressures (in static condition on the same height) and their coherence is depicted in Fig. 4, the coherence result shows that there is a relation between the two pressures in the low-frequency band, which led us to apply exponentially weighted low pass filter with a half-life = 20 samples to both signal with the aims to locate the signals in the area of higher similarity. Increasing the similarity also increase the possibilities of a linear fitting between the two pressures.

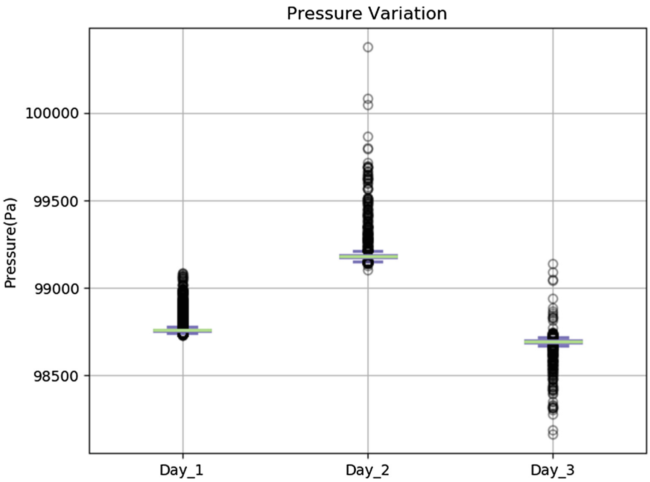


**Fig. 3.** Pressure variation in 3 days

When the goal is to have a precision of less than one meter it is important to also make the stationary Test (Dickey-Fuller test), because a variation of only 1 Pa in the pressure means an 8 cm difference relative to sea level, and even more with a variable standard deviation, then a linear fitting is only valid in the situation it was calculated. The results of the stationary Test for both signals in Fig. 4 is shown in Table. 1, the Test was applied for the 3 different days in static condition, the Reference-device (RDevice) pressure was 95–99% stationary, ($Test < CriticalValue(1\%)$), and for the Wearable-device (WDevice) pressure was 90–95% stationary ($Test < CriticalValue(5\%)$), despite that the results are almost stationary, we observed that the pressure values were different for each day and that the offset difference between the RDevice and the WDevice is not constant, go to Fig. 3. From the similarity and stationary results, the most simple version for the model will be a linear model, as in Eq. 2.

$$WDevicePressure = a * RDevicePressure + offset \tag{2}$$

The data in Fig. 4, was divided into 70% training and 30% test, RANSAC, and Polynomial Fit methods were used, and the results are presented in the Table.2. The minimum mean-squared error = 4.27 Pa(an approximated value of

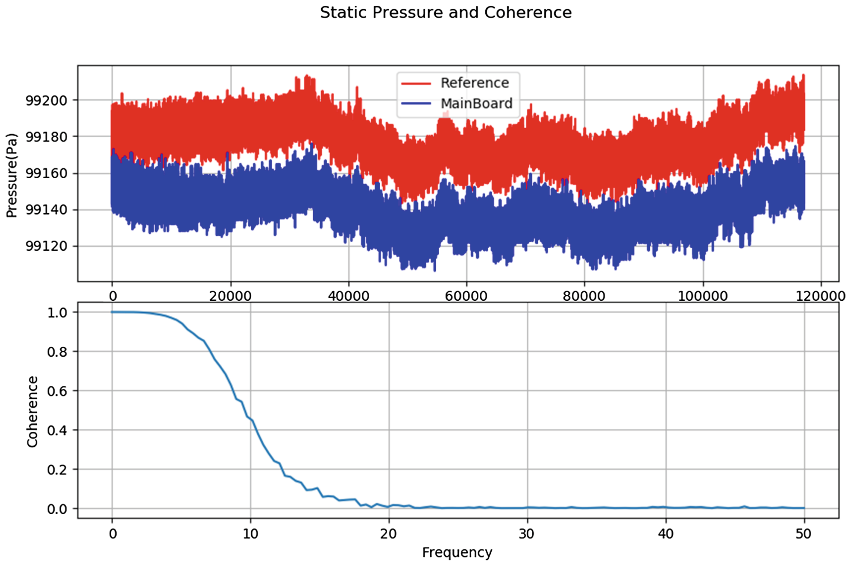


**Fig. 4.** Reference device pressure(red) and Wearable Device pressure(blue) and the coherence of the signals (Color figure online)

**Table 1.** Stationary test results

| Reference board | Wearable board |
|---|---|
| Test = –3.44 | Test = –3.17 |
| p-value = 0.0096 | p-value = 0.022 |
| Lags = 71 | Lags = 71 |
| Observations = 118265.0 | Observations = 118265.0 |
| Critical-value(1%) = –3.430405 | Critical-value(1%) = –3.43 |
| Critical-value(5%) = –2.86 | Critical-value(5%) = –2.86 |
| Critical-value(10%) = –2.57 | Critical-value(10%) = –2.57 |

33 cm, relative to the sea level pressure) was from the RANSAC test as shown in Table 2.

$$a = 0.97 \tag{3}$$

Also, the proposed solution for the offset calculation is to use an error-monitor option(RFID-Barometer at reference point), so the difference is measured at the beginning, and then every time the WDevice is in RDevice position. The monitor-error option selected is a simple but widely used RFID Tag-Reader combination for picking order activities like in [1,10,13].

**Table 2.** Linear fitting results

| RANSAC | Polynomial |
|---|---|
| Mean-squared-error = 4.27 | Mean-squared-error = 4.47 |
| Variance-score = 0.95 | Variance-score: 0.94 |

## 3 Setup and Experiments

To evaluate the system, two scenarios were tested, the first one as order-picking inside a warehouse (Warehouse-Box Experiment)which involved the movement of a box between a compartment and a reference position (a table, simulating an order-picking car), and the second scenario as the movement of the arm around the upper, middle and lower part of the body in daily life activities (Body-Experiment). For the Warehouse-Box Experiment, a shelf of six compartments and a table simulating an order picking car was used. Five volunteers were asked at the beginning to go to the reference (RFID-Barometer on the table), and later on to take a box and put the box inside each compartment randomly (10 picking-actions per compartment) and wait there between 3–5 s, each time returning to reference, waiting again on the reference 3–5 s. The maximum compartment height is 28 cm, and the distance of the reference point to the ground is 85.4 cm, the heights of the volunteers in decreasing order were: 197,190,177,170,157 cm. For the Body-Experiment, the reference point was set around the pocket (RFID-Barometer on the pocket), and the person needed to start again at the reference and then go to the upper body part (Head), body middle part (Heart) and body lower part (Foot) randomly (also, 10 repetitions per position), and every time going back to reference. In addition, the use of the RFID as monitor of the reference location, was tested with 3 participants, where two of them pick-up an object 30 times and went back to the table and the third participant did this 50 times, in all of the cases the RFID captured 100% of the picking actions, which means the RFID is a good enough to be a monitor device.

### 3.1 Identification by Naive Bayes Classifier

To quantify the accuracy of the system a naive Bayes classifier was used, due to the Gaussian behavior shown in the height estimation using barometer pressure, please go to Fig. 5. Each picking action was divided into frames of 12 samples (0.192 s, 16 ms/sample), from which statistical features as mean, standard deviation, maximum and minimum were calculated. In the case of the Warehouse-Box Experiment, the model was done using 1 min of static data from each compartment, and tested with five volunteers, in which the best case was 62,86% accuracy, and the worst case was 56.81% accuracy. The confusion matrix from the best case can be seen on the left side of Fig. 6. With regard to the body experiment, we tested 3 model scenarios, in the first scenario the model was based on

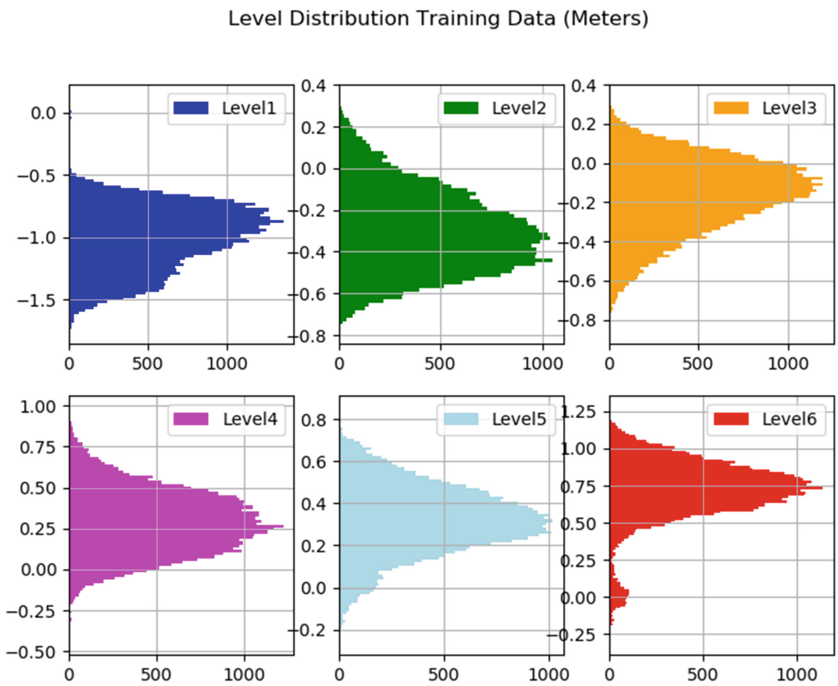


**Fig. 5.** Level distribution (vertical axis in meters) from the warehouse-box experiment.

the volunteer with the middle height, 177 cm(70% training), getting an accuracy scores of 82.03% (volunteer's height = 170 cm), 91.48% (volunteer's height = 177 cm) and 73.05% (volunteer's height = 190 cm). In the second scenario the model was based on the participant with a height = 170 cm (70% training), given accuracy results of 87.28%, 81.82% and 78.81% (In height increasing order). In the last scenario the model was based on the volunteer with height = 190 cm, with accuracy results of 86.39%, 85.23% and 84.25% (In height increasing order, the confusion matrices of the participants on the third scenario are shown in Fig. 7, this third scenario is the one with less variation on accuracy.

In order to compare our results, the same classifier with a model based on static data and an initial offset correction but without the RFID information was applied to the same data. The calculated height was directly the relative value between the RDevice and WDevice pressures, the resulted confusion matrix is shown on the right side of Fig. 6, in this case, only the drifting and the sudden changes on the pressure errors are considered. No paying attention to the offset dependency decreased the accuracy to 48.61%, and the identification of the middle levels are highly affected.

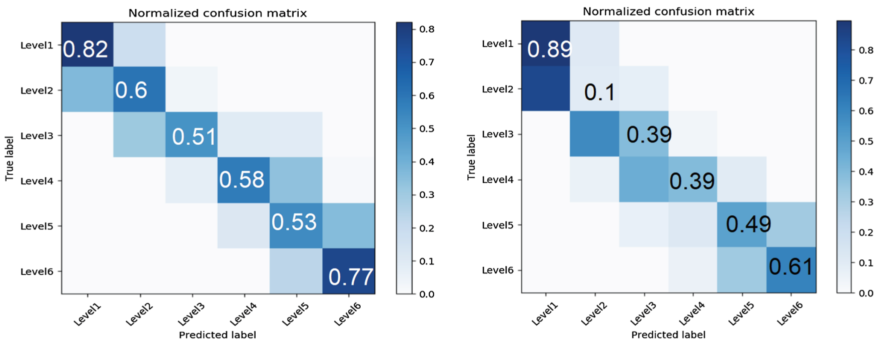


**Fig. 6.** Confusion matrix of the best case from the warehouse-box experiment using RFID-monitor error method(Left side), and without using RFID information(Right side)

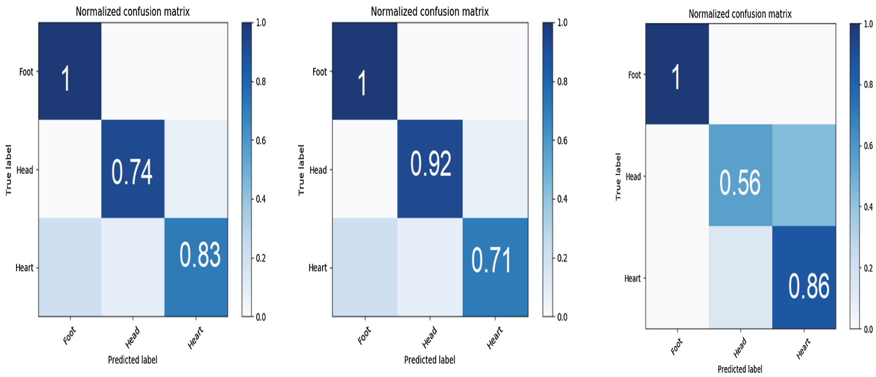


**Fig. 7.** Volunteer 1 (170 cm), Volunteer 2 (177 cm) and Volunteer 3 (190 cm) confusion matrices from the body-experiment

## 4 Results and Contributions

The use of relative height estimation by barometer pressure differences and the RFID as a monitor-error method improved the detection of the vertical position compared to using the barometer-height relationship without RFID, in which the dependency of the drifting, humidity and temperature were not taken into account. This goal was achieved by only using a simple linear model and an RFID chip to calculated the initial offset and to reduce the impact of the drifting and offset in the vertical position estimation, additionally to the reduction of the effects of sudden changes on pressure, due to the opening of windows or doors around the devices. This initial step could evolve into a fusion of sensor to obtain more accurate results. An important point to consider is that the prototyping hardware has a height of 11 cm, which means that the error will be on the measurement depending on the orientation of the wrist in the picking action.

Moreover, the linear fitting has a minimum mean-squared error of 4.27 Pa. For the simplicity and limitations of the system, this first step achieved relatively good results.

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