BaR: Barometer based Room-level Positioning

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***Abstract*—We introduce a new barometer based room-level positioning system called BaR. This system monitors the air pressure in different rooms to identify the position of mobile sensors with room-level granularity. To disregard air pressure perturbations caused by the environment, BaR relies on a partial correlation of the barometer values and focuses only on the intrinsic relations between the mobile and room sensors. Our preliminary experiments demonstrate the potential and benefits of BaR using very cheap barometers already available in smartphones.**

I. Introduction

Nowadays, mobile devices offer numerous location-based services such as navigation systems, location-based games, and location-based advertisements. Global Positioning System (GPS) is the main technology providing location data to these services. Despite its success, worldwide coverage, and accuracy, GPS is not able to locate devices within buildings.

Consequently, indoor positioning has received a lot of attention and multiple approaches have been proposed, for example, using WiFi access points, Bluetooth Low Energy (BLE) tags, computer vision, and Ultra-Wide Band (UWB). As summarized in Table I, each method has different advantages and disadvantages. Some of these methods rely on markers that are either set up at known locations or used as landmarks in a learning phase.

For example, Rekimoto et al. proposed the PlaceEngine [1], which estimates location using the Received Signal Strength Indicator (RSSI) values of WiFi radio signals received from nearby access points. Because it uses already available WiFi access points, implementing this system is fairly cost efficient. In addition, it is also fairly accurate and provides wide coverage in a room, but it may not work behind walls or metal obstacles.

Ubisense [2] is a three-dimensional localization service based on UWB. It provides 150-mm accuracy. Similar to PlaceEngine, obstacles are detrimental to Ubisense as they block the high-frequency radio wave signals. On the market, there are also several providers selling ultrasonic beacons and accompanying software for mobile phones. Each beacon covers a limited area and the system requires numerous beacon modules when the target room is large.

In this paper, we tackle the indoor positioning problem by monitoring the fluctuations of air pressure in several rooms, mainly caused by opening or closing doors and air conditioning. The proposed Barometer based Room-level (BaR) positioning system locates mobile devices at room-level granularity, requires only one sensor per room, and is not sensitive to physical obstruction. In our experiments, we show that using data from two pressure sensors, we can determine whether the two sensors are in the same room. We argue that a precise room-level positioning system is potentially more practical than indoor coordinate systems for applications requiring contextual information. For example, an application might only be interested in knowing if the mobile device is inside a shop or not or whether members of an audience are in a conference room or not.

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TABLE I
Comparison of indoor positioning systems

	WiFi	UWB	Ultrasonic	BaR
Accuracy	✓✓	✓✓✓	✓✓	✓
Range	✓✓	✓✓✓	✓	✓✓✓
Obstruction	✓	×	×	✓✓✓

TABLE II
Specifications of barometers

Vendor	Paroscientific	OMRON
Product	1600-102 [1]	2SMPB-02B [2]
Range [kPa]	80–110	30–110
Accuracy [Pa]	±8	±100
RMS Noise [Pa]	0.495	3.7
Sampling [Hz]	100	90
Size [mm]	67 × 67 × 57	2 × 2.5 × 0.85
Price range [USD]	10,000	1 or less

II. Background and Datasets

In this section, we demonstrate the benefits of air pressure for indoor positioning using a very accurate barometer. Because this barometer is both expensive and cumbersome, we then investigate the usefulness of a cheaper Micro Electro Mechanical Systems (MEMS) sensor that is commonly found in handheld devices. We verified the performance of the MEMS sensor and found that its accuracy is sufficient for our proposed method.

A. Air pressure change

To accurately monitor the air pressure fluctuations in a room, we first employed a precise pressure sensor produced by Paroscientific (see the specifications in Table II).

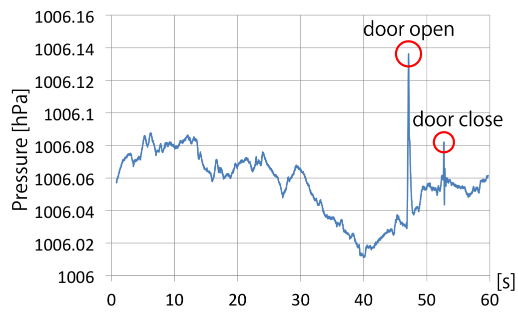

Fig. 1. Air pressure changes in a room (with opening/closing door events)

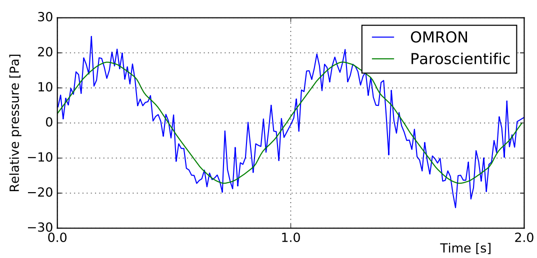

Fig. 2. OMRON and Paroscientific sensor results for 1 Hz sine wave pressure changes

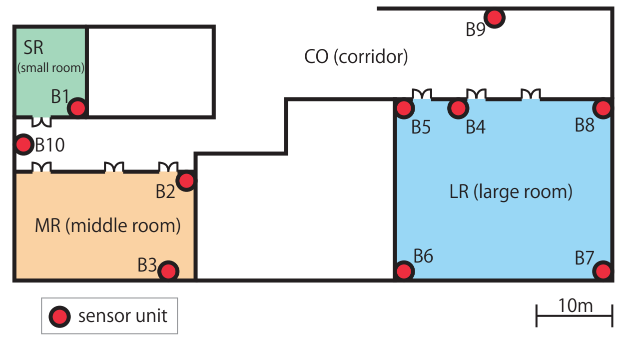

Fig. 3. Floor plan of the sensor unit locations

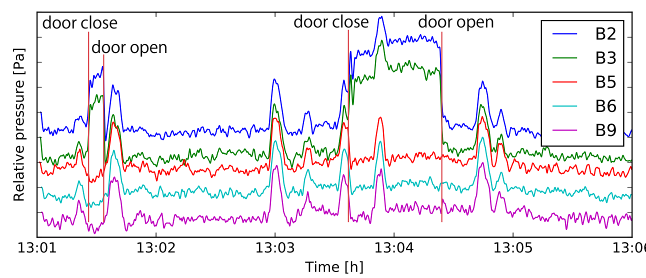

Fig. 4. Typical sensor waveform (0.5 Hz low-pass filtered)

We set up this sensor in a room, on a table located 2 m away from the door. Figure 1 shows the air pressure recorded by the sensor. The air pressure is constantly fluctuating because of environmental factors such as weather changes and turbulence from the air conditioning fan.

Two apparent events are also shown in Figure 1. One is the clear 10 Pa height peak-to-peak narrow pulse at 47 s that is due to the opening of the door, and the other is the 4 Pa height peak-to-peak damped oscillation at 52 s due to the closing of the door. These patterns manifest activities occurring in the monitored room and are the basic elements monitored by BaR to identify sensors located in the same room.

B. *Usefulness of cheaper barometers*

From our experiments with the Paroscientific sensor, we derived two sensor requirements. To detect common events in a room, the noise level of the sensor should be lower than 5 Pa and the sampling period should be shorter than 0.02 s. Consequently, for more realistic experiments, we selected a barometer that satisfies these requirements and is already embedded in numerous smartphones. This sensor is produced by OMRON and its specifications are shown in Table II.

We further validated the accuracy of the OMRON sensor by comparing its results to those obtained from the expensive Paroscientific sensor. Both sensors were placed in the a chamber box with a speaker on the opening of the box. Figure 2 illustrates the results obtained from both sensors when a sine wave is emitted from the speaker. We found that both sensors capture the same waveform without any obvious delay. The noise level of the OMRON sensor is much larger than that of the other sensor, but it records the 1-Hz sine wave air pressure changes with enough accuracy to detect events such as opening and closing doors. In addition, the OMRON sensor has obvious practical advantages such as its size and price.

[1]Digiquartz Broadband Intelligent Instruments with RS-232 and RS-485 Interfaces User Manual by Paroscientific, Inc. DOCUMENT NO. 8819-001, REVISION AB, JANUARY 2016

[2][2SMPB-02B] Datasheet JP Rev. 21 (Sep., 2016) by OMRON Corporation

C. *Experimental setup*

In this study, we present results obtained during a three-day meeting in a hotel. We setup eight sensors in three meeting rooms and two sensors in the corridor. The sensor positions are depicted by red points in Figure 3. In addition, we setup a mobile sensor that was moved during the experiment. The clocks of all sensors were synchronized using the Network Time Protocol (NTP). We collected 29 data sets, each of them lasting from 1 to 60 mins and containing the 10-sensor data and the mobile sensor data.

We also recorded ground truth data for the position (room number) of the mobile sensor. For more than half of the data sets, the mobile unit remains in the same room. In the other data sets, the mobile sensor moves from one room to another.

III. System Design

A. *Challenge*

Our goal is to estimate the location of a mobile sensor by comparing its barometric values to those obtained from other sensors with known positions. Figure 4 shows an example of data collected for a set of selected sensors from our experimental setup (Section II-C). Signals are vertically shifted

TABLE III
NOTATIONS

M	Number of reference units
S'_0	Normalized signal of the mobile sensor unit
S'_m	Normalized signal of the mth reference unit ($m = 1, \cdots, M$)
$P(X, Y, Z)$	Partial correlation coefficient
L	window size [s]
f	Low-pass filter frequency
τ	Threshold value

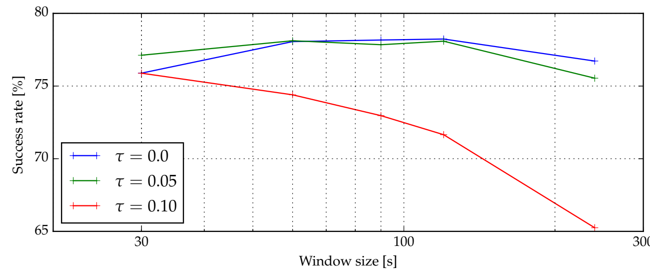

Fig. 5. Correct room estimation rate versus data window size (s)

to enhance the readability of the figure. The "door close" annotations mean that all doors in the middle room (MR) are closed at that time. In addition, "door open" annotations mean that one door in the MR is open at that time. Although sensors are located in different rooms, we observe common air pressure spikes across all sensors. These are caused by environmental factors such as air conditioning, and are detrimental for our study. Nevertheless, we found that the activation of the MR doors affects only the air pressure in the MR (see B2 and B3 in Fig. 4). Therefore, the main challenge we are facing is to disregard the patterns found in all signals and pay more attention to uncommon, yet significant, fluctuations. As explained in the rest of this section, BaR primarily relies on the partial correlation measure to overcome this challenge.

B. Methodology

Let $S_0(t)$ denote the signal from the mobile sensor and $S_m(t)$ denote the M signals from the fixed reference sensors. First, we normalize these signals by subtracting their mean value and dividing by their standard deviation. The normalized signals are denoted by $S'_0(t)$ and $S'_m(t)$. Second, for each reference sensor m, we compute

$$P_m(t) = P(S'_0(t), S'_m(t), Z'_m(t)), \tag{1}$$

which is the partial correlation of sensor m with the mobile sensor using other signals as controlling variables, $Z_m = \{S'_k \mid m \neq k\}$.

One can simply estimate the position of the mobile sensor by determining the maximum correlation value

$$o(t) = \arg \max_{1 \leq k \leq M}(P_k(t)). \tag{2}$$

However, (2) only relies on the maximum value and disregards the values from other sensors. To measure the distance between the maximum correlation value and average correlation value, we use function $e(t)$, defined as:

$$e(t) = \max_{1 \leq k \leq M}(P_k(t)) - \frac{1}{M}\sum_{k=1}^{M}(P_k(t)), \tag{3}$$

$$o'(t) = \begin{cases} o'(t - \delta t) & (e(t) \leq \tau) \\ o(t) & (otherwise) \end{cases}. \tag{4}$$

If the maximum correlation value deviates substantially from the average correlation value (i.e., the difference is higher than an arbitrary threshold value τ), then the mobile device is mapped to the corresponding room. Otherwise, the estimated room corresponds to the previous estimation.

In our experiments, certain rooms contain more than one sensor. To simplify computation, we merge sensors from the same room by averaging their values. In addition, the above process is operated within a sliding window of size L. Signals are low-pass filtered with a corner frequency of f. In the next section, we investigate the sensitivity of our method to this parameter and threshold τ.

IV. EVALUATION

Using the experimental setup presented in Section II-C, we estimated the position of the mobile sensor for the 29 data sets. We optimized the window length and low-pass filter frequency to achieve better estimation results. As for the low-pass filter, we estimated low-pass filter between 0.1 Hz to 30 Hz by evaluating average sucess ratio across all data sets. we found that the 30 Hz filter gives the best success ratio.

We define the success rate as the proportion of correct position estimations to all estimations computed for one data set. Figure 5 shows the relationship between window size L and the average success ratio across all data sets. We also varied the value of the threshold (0.0, 0.05, and 0.1) to determine the method's sensitivity to this parameter.

The maximum correct room estimation rate is obtained with window sizes ranging from 60 to 120 s. Using shorter window sizes allows us to detect faster device movements, thus, for the remaining experiments, we selected a window size of 60 s and both 0.0 and 0.05 for the threshold values. The three lower plots in Figure 6 show the estimation results with these parameters.

Figure 6 (left) shows the case where the mobile sensor stays in the MR while the doors open and close. The upper figures show the partial correlation between the values of the mobile sensor and each room's fixed sensor. We can confirm that the mobile sensor and MR sensor are strongly correlated while the correlation with other rooms is relatively weak. The lower graph shows that BaR correctly identifies the room where the mobile sensor is located. Only one error occurred when the threshold was set to 0.0 and no error occurred when it was set to 0.05.

The center plots of Figure 6 show the case where the mobile sensor is located in the large room (LR). The partial correlation

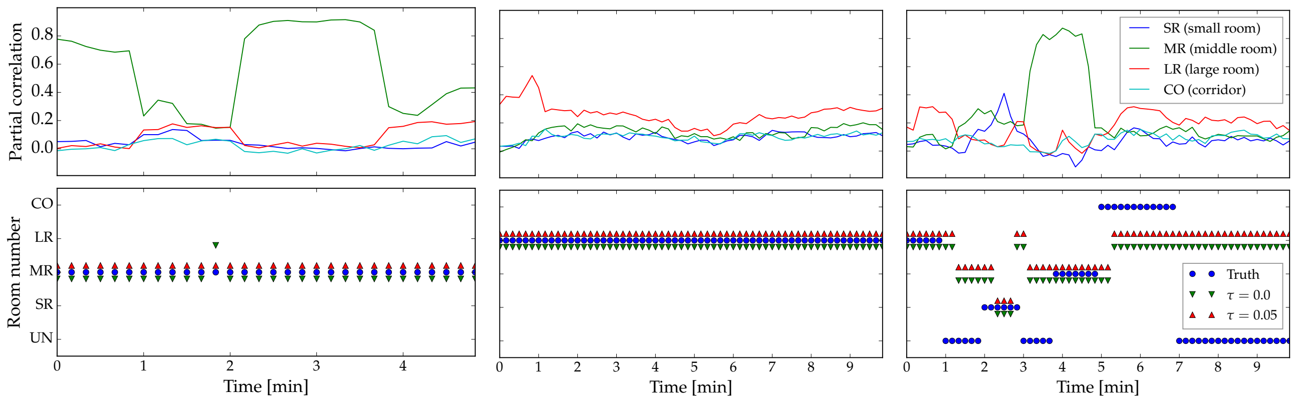

Fig. 6. Partial correlation values and BaR estimation results. Left and center: the mobile sensor remains in one room. Right: the mobile sensor moves to different rooms. "UN" indicates that the position is unknown.

with the LR sensors is higher than for other rooms. After the first 30 s, the LR door is closed and opened and, as a result, the correlation value of the LR becomes the highest in this figure. The room numbers are correct for all estimation points. This example also shows that when the door is left open, BaR estimates the correct room number.

The right plots of Figure 6 illustrate an example in which the mobile sensor moves across different rooms. At the beginning, the mobile sensor is in the LR, then it moves to the small room (SR) and MR. The estimation points also show many correct room numbers. However, there are also some incorrect estimations. After the first five minutes, the mobile sensor is actually in the corridor (CO), but the LR is the estimated room. From our experiments, we found that BaR detects the correct room number if the mobile unit is in a room. However, when the mobile sensor is in the CO, BaR usually struggles to estimate the correct location of the mobile sensor.

V. Related Work

A few researches have also investigated the usability of air pressure for positioning systems.

At a global scale, for example, the Comprehensive Nuclear Test Ban Treaty Organization operates the Infrasound Monitoring System (IMS) [3]. Infrasound is sound at a frequency that is lower than a human can hear. IMS measures the micropressure changes in the atmosphere that are generated by nuclear explosions. There are 60 such stations around the world, and each station estimates the direction of the sound source, then it integrates all these outputs to find the location of the sound source. A similar method is used for scientific research for volcano explosions.

As for indoor positioning research, Ahn and Lee [4] proposed a positioning system using ultrasound and infrasound. This system makes a sound map that is used to locate the position in a room. Bauer et al. [5] also investigated the potential use of infrasound for indoor positioning. Strozzi et al. [6] used a barometer with Inertial Measurement Unit, and the barometer detected any change in altitude and detected the floor level. However, this method was not used to find the device location.

VI. Conclusion

In this paper, we introduced the potential of barometer-based indoor positioning. In our experiments, the proposed method, BaR, estimated correct room numbers in multiple situations. The success rate of BaR is currently around 78%, which is promising but far from perfect. We believe that the use of barometers in conjunction with other positioning systems could provide very precise indoor positioning, as the source of information is drastically different. In future work, we plan to evaluate the proposed system in diverse environments and refine our methodology.

Acknowledgment

The authors would like to thank to Mr. Takuma Oi and Toho Mercantile Co. Ltd., who supported our research by providing the chamber box and Paroscientific sensor and helping with sensor calibration.

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