

# Estimate a User's Location Using Smartphone's Barometer on a Subway

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## ABSTRACT

Knowing the location of a train is necessary to develop a useful service for train passengers. However, popular localization methods such as GPS and Wi-Fi are not accurate especially on a subway. As an alternative method, estimation of motion state and stop station by using sensors on a smartphone is being studied for subway passengers. This paper proposes a localization method that uses only a barometer on a smartphone. We estimate motion state from the change of elevation, and also estimate latest stop station by the similarity of a series of elevations recorded when the train stopped and actual elevations of stations. By estimation of the motion state and the latest stop station, development of various context-aware services for subway passengers becomes possible. Through experiments in four lines of subway in Tokyo, we demonstrated that the accuracy of estimation of the motion state is 86%, and estimation of the stop station is 58%.

## Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous;  
I.5.4 [Computing Methodologies]: Pattern Recognition—  
*Waveform analysis*

## General Terms

Algorithms, Experimentation

## Keywords

Barometer, Location Estimation, Subway, Smartphone

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MELT'15 November 03-06, 2015, Bellevue, WA, USA

© 2015 ACM 978-1-4503-3968-1/15/11 ...\$15.00

DOI: <http://dx.doi.org/10.1145/2830571.2830576>.

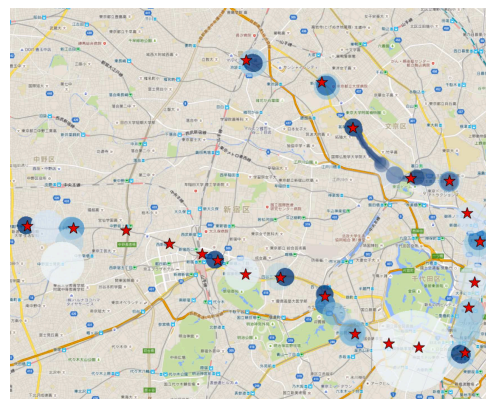


Figure 1: Map of location information that could be obtained while riding the Tokyo Metro Marunouchi line (scale 1:45800). Red stars are the position of the station. Blue circles are the location that it could be obtained. Its size and depth of color represents the precision.

## 1. INTRODUCTION

In the last decade, subway passengers are getting more eager to use digital gadgets such as a music player, a handheld game console, an e-book reader and a smartphone [1]. Especially in recent years, utilization of a smartphone is popular as enabling wireless communication is becoming available even under the ground. A passenger can get any information anytime even while riding a subway train nowadays.

A subway passenger, however, cannot obtain current location information that many applications for a smartphone depend on because of poor GPS signal on subway. Wi-Fi-based localization also does not work well due to the lack of Wi-Fi stations and the inaccuracy of the database. Figure 1 illustrates location information that we obtain while riding Marunouchi subway line. The location information we obtained is limited and often differs from the actual location.

If location information is available in the subway, there

are many opportunities to develop applications such as to announce the next stop, to provide directions after exiting the entrance of the station in advance and to notify when a user needs to get off while reading a e-book. Since a train does not always run exactly following the timetable, obtaining the position of train in the underground is an important issue.

In this paper, we estimate location of a subway train by using only the barometer in a smartphone. The latest smartphones such as Apple iPhone 6 and Samsung Galaxy are equipped with a barometer. The proposed method firstly estimate if the train is running or stopped by the amount of the change of air pressure. Then, we estimate the exact station the train is stop by the elevation. We accomplished 58 % accuracy in the estimation.

## 2. RELATED WORKS

In recent years, many subway passengers use a smartphone. [2] estimates the position of train by using accelerometer and timetable. [3] estimates the motion state by using accelerometer and magnetic sensor. Method using an accelerometer is necessary to complex processing for noise removal because it is sensitively affected by the way to hold a smartphone. Method using a barometer can simply use measured values because it is not affected by the way to hold. [4] estimates the stop station from the similarity of the change of air pressure while running between stations. The method cannot determine if the train is running or stopped automatically. It also cannot always match the correct pattern because of the change of air pressure by the influence of the opposite side train. [5] is context detection using a barometer. They determine only whether riding on the subway. In this paper, we determine riding train's motion state (i.e., stopped or running).

## 3. METHODOLOGY

This research aims to accomplish localization in a subway by using only a barometer on a smartphone. The change of air pressure is a good clue to localize a smartphone because we can estimate both motion state (i.e., stopped or running) of the train and the exact station while stopping from the air pressure. The air pressure basically changes with the altitude, but it swings rapidly in a tunnel due to Bernoulli's principle. When a train stops, the change becomes relatively stable, and the value reflects the altitude of the station. With these phenomena, we estimate the location of the subway train.

### 3.1 Calculation of altitude

Firstly, we calculate the altitude from the air pressure measured by barometer on a smartphone using the following formula[6].

$$h = 153.8 \times (t_0 + 273.2) \times \left(1 - \left(\frac{P}{P_0}\right)^{0.1902}\right)$$

$h$  [m] is the altitude,  $t_0$  [°C] is the sea-level temperature,  $P_0$  [hPa] is the sea-level air pressure, and  $P$  is the measured air pressure. In this paper, we utilize the latest temperature and air pressure provided by the Japan Meteorological Agency.

We conducted a preliminary experiment on the accuracy of elevation measured by using a barometer in a smartphone. We measured the elevation while going up and down in the elevator between the eleventh floor (elevation about 45m)

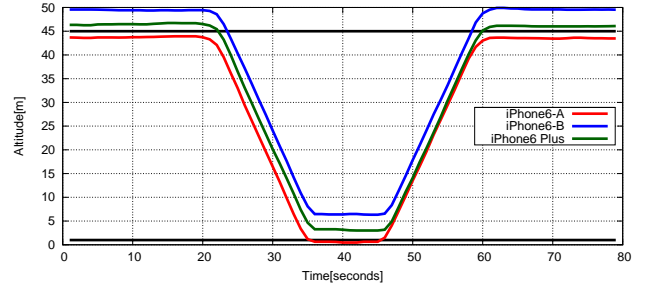


Figure 2: Altitude calculated from air pressure measured in elevator

and the first floor (elevation about 1m) with two iPhone 6 and one iPhone 6 plus. Figure 2 illustrates the result. A sampling rate of the barometer in the iPhone 6 is 1.32 seconds. A relative change in elevation of each device fits to the true difference in elevation, but the absolute elevation in each device is different. Therefore, we use the relative change of elevation rather than the absolute elevation except for the estimation of the first stop station.

### 3.2 Estimation of motion state

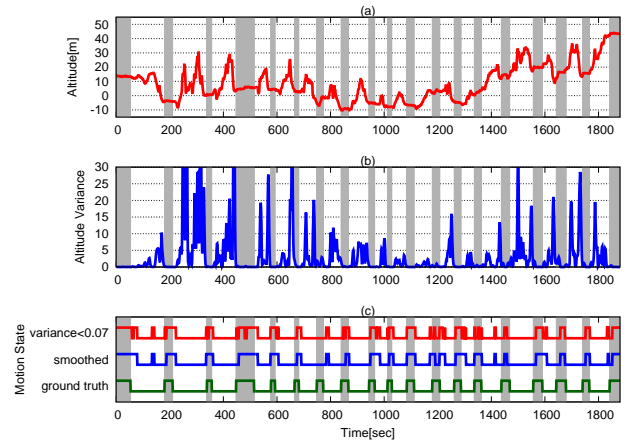


Figure 3: Estimation of motion state: (A)altitude (B)variance (C)Estimated motion state. Gray area is actual stop time

Secondly, we estimate train's motion state (i.e., *RUNNING* or *STOPPED*) by variance of estimated altitude. In the following, we explain the detail with the result of the experiment when we ride a subway train in Chiyoda Line in Tokyo illustrated in Figure 3. Figure 3(A) shows the altitude calculated from the air pressure. The altitude changes with the influence of the tunnel as well as the actual elevation of the line. As an indicator of the change of altitude, we calculated the variance of altitude in last 10 samples (13.2 seconds). Figure 3(B) illustrates the variance of altitude. When the variance exceeds a certain threshold, we can suppose that the train is *RUNNING*, and when it is less than the threshold, we can suppose the train is *STOPPED*. In this paper, we adopt 0.07 as a threshold. In the center of Figure 3(C) illustrates the result of the decision of the motion. We smooth the result by omitting frequent change of

the state from the naive judgment.

### 3.3 Estimation of stop station

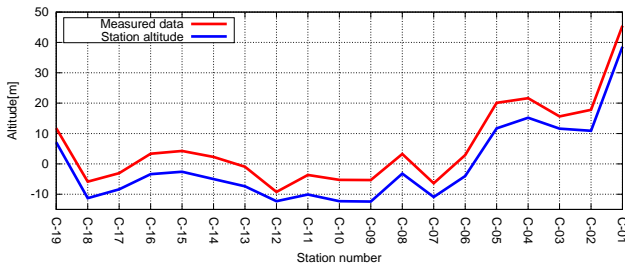


Figure 4: Measured altitude and the actual altitude

Finally, we estimate the station the train is stopped by the similarity of a series of recorded altitudes and the true altitudes of stations. Figure 4 illustrates the true altitudes and altitudes calculated from the air pressure in Chiyoda line assuming that estimation of stop station works ideally. Although the absolute elevations are different, the change in elevation is similar. Therefore, it is possible to determine the stop station if we detect the motion state exactly. There are 13 lines in Tokyo, and we assume that the line and direction of the riding train are given in advance, which can be obtained from an application such as the Google transit.

The proposed method records an altitude when the motion state changes from *RUNNING* to *STOPPED*. After passing two or more stops, the method calculates the similarity between (A) last  $n$  records of altitudes and (B) every  $n$ -length subsequence of the true altitudes of the stations in a certain line. In order to compare the relative change of the altitude, the method subtracts the average of A and B from each element of A and B respectively. Then the method calculates a cosine similarity with the following formula.

$$\text{similarity} = \frac{\sum_{i=1}^n A_i \times B_i}{\sqrt{\sum_{i=1}^n (A_i)^2} \times \sqrt{\sum_{i=1}^n (B_i)^2}}$$

The last station of the section that has the maximum similarity is the estimated station.

## 4. EVALUATION

### 4.1 Experimental procedure

Table 1: Information of experimented lines

line (prefix)	sta- tions	altitude[m]			time [min.]
		min	ave	max	
Marunouchi(M)	25	-7.3	17.6	36.3	50
Hanzomon(Z)	14	-28.9	-10.6	25.5	30
Chiyoda(C)	18	-12.4	-1.0	38.6	38
Hibiya(H)	21	-16.8	-2.9	19.2	30

To evaluate the proposed method, we conducted an experiment to record the air pressure and true motion state with an iPhone application that we developed. We collected data

of three round-trips in each of four lines out of 13 lines of subway in Tokyo (Table 1). In the experiment, we utilized two iPhone 6. We inputted the true motion state manually every time the train stopped and start running at the station. The true motion state is not based on the open/close of the door, but the actual movement of the vehicle.

### 4.2 Motion state estimation

We evaluated the accuracy of estimation of motion state by seeing if a time interval estimated to be stopped overlaps with the true stop at a station. If there is more than one estimation of stop at a single station, we regard subsequent estimations as being incorrect. We calculated precision, recall and F-measure where the precision is (number of correct estimations / number of stop estimations), the recall is (number of correct estimations / number of stations), and the F-measure is  $(2 \times \text{precision} \times \text{recall}) / (\text{precision} + \text{recall})$ .

Table 2: Performance of motion state estimation

line		precision	recall	F-measure
Marunouchi (M-01~M-25)	asc	0.913	0.973	0.942
	desc	0.864	0.973	0.914
Hanzomon (Z-01~Z-14)	asc	0.917	0.929	0.916
	des	0.735	0.857	0.791
Chiyoda (C-01~C-19)	asc	0.788	0.912	0.845
	desc	0.801	0.947	0.866
Hibiya (H-01~H-21)	asc	0.669	0.952	0.786
	desc	0.775	0.937	0.846
total		0.808	0.935	0.863

Table 2 illustrates the experimental result of motion state estimation. Recall is from 85% to 97%. Most of the stops at stations is estimated to be *STOPPED*. On the other hand, precision is from 67% to 92%. In this experiment, the method confirms that the train is really *STOPPED* only after three times continuous detection of being *STOPPED* because the distance between stations is often short. This is why we cannot omit misestimating of being *STOPPED* while running the subway train.

### 4.3 Stop station estimation

The accuracy of estimation of the stop station is evaluated by the rate of the accurate estimation. The number of the stations used for the estimation is  $n$ , and the accuracy rate is defined as (the number of correct estimations / (number of stations -  $n + 1$ )).

We first evaluated the accuracy with the assumption that the estimation of motion state works perfectly in order to evaluate the pure performance of the station estimation. Table 3 illustrates the accuracy of the estimation based on the elevations when a train exactly stopped. Accuracy rate was 67% on average. The more stations the estimation method utilizes, the higher accuracy the estimation has.

We then evaluated the accuracy with the actual result of estimation of motion state that contain several errors. Table 4 illustrates the accuracy of the estimation based on the elevations when a train is estimated to stop. Accuracy rate was 50% on average, and it is very different by the line. In the line whose accuracy of motion state is low, the accuracy of station estimation is also low. The accuracy is not so much improved even if the number of station using for estimation is increased. In order to improve estimation

**Table 3: Accuracy of station estimation (based on elevation when the train exactly stopped)**

line		accuracy rate			
		n=2	n=3	n=4	n=5
Marunouchi (M-01~M-25)	asc	0.278	0.565	0.742	0.825
	desc	0.319	0.536	0.636	0.762
Hanzomon (Z-01~Z-14)	asc	0.359	0.861	0.939	1.000
	des	0.282	0.722	0.788	0.933
Chiyoda (C-01~C-19)	asc	0.481	0.686	0.750	0.844
	desc	0.407	0.627	0.813	0.889
Hibiya (H-01~H-21)	asc	0.400	0.684	0.815	0.882
	desc	0.417	0.561	0.704	0.765
total		0.367	0.636	0.759	0.847

**Table 4: Accuracy of stop station estimation (based on the motion state estimation)**

line		accuracy rate			
		n=2	n=3	n=4	n=5
Marunouchi (M-01~M-25)	asc	0.348	0.515	0.619	0.667
	desc	0.290	0.455	0.571	0.633
Hanzomon (Z-01~Z-14)	asc	0.333	0.818	0.833	0.778
	des	0.333	0.424	0.367	0.333
Chiyoda (C-01~C-19)	asc	0.392	0.583	0.644	0.714
	desc	0.373	0.646	0.533	0.619
Hibiya (H-01~H-21)	asc	0.281	0.352	0.431	0.417
	desc	0.421	0.537	0.510	0.521
total		0.327	0.498	0.527	0.553

of stop station, we need to improve the method to estimate the motion state of the train.

## 5. DISCUSSION

### 5.1 Advantage from the related works

This research aimed to accomplish localization on a subway for practical service by using only a barometer on a smartphone. The result of the experiment is inferior to the related works in terms of the estimation of the motion state or stop station, but related works are not suitable for practical services. [3] needs long-term data including future time for the determination of a certain time because of smoothing and peak detection. [4] needs additional technique to identify if the train is running or stopped. On the other hand, the proposed method can determine a motion state immediately after starting the application because we utilize only the air pressure of past few seconds. Therefore, although it is needed to improve the accuracy, the proposed method is effective to estimate a train’s motion state and latest stop station to develop practical services for subway passengers based on the location.

### 5.2 Erroneous estimation of motion state

The erroneous estimation of the motion state is caused by several reasons. First, a train in the opposite track affects stop decision because it causes a change of air pressure. The motion state is determined to be *RUNNING* by the movement of the opposite train even though the current train has stopped. Secondly, the optimal parameter is different depending on the line. If we require much longer repeat of the same motion state when smoothing, erroneous deci-

sion is reduced. But in this paper, we set the number of necessary repeat considering the shortest distance between stations within every subway line. As a result, it had many erroneous determinations that are not smoothed. Thirdly, there are ground sections in a subway line. This causes the incorrect stop detection because the change of air pressure is small on the ground. We need to combine other sensors on a smartphone, and change parameters to estimate dynamically to improve the method.

### 5.3 Erroneous estimation of stop station

The erroneous estimation of the stop station is mainly caused by the error in the estimation of the motion state. In addition, the change of measured air pressure does not completely fit to the true altitude of the stations. We need to study other factors that affect the air pressure such as air conditioning, congestion and the position within the train. We can also utilize location information of a smartphone to filter the result of the estimation even though it has a large error.

## 6. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a real-time estimation method of train’s motion state and the latest stop station by utilizing only a barometer on a smartphone. We estimate train’s motion state and latest stop station from the change of air pressure. Through the experiments in four lines of subway in Tokyo, we showed that the accuracy of estimation of the motion state is 86% on average, and estimation of the stop station is 58% on average. As a future work, we will improve the accuracy of decision by using other sensors and rough location information. We also study to estimate riding line and direction automatically.

## Acknowledgments

This work was conducted as a part of NICT Social Big Data Project.

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