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A Two-step Kalman/Complementary Filter for Estimation of Vertical Position Using an IMU-Barometer System

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Abstract—Estimation of vertical position is critical in applications of sports science and fall detection and also controls of unmanned aerial vehicles and motor boats. Due to low accuracy of GPS(global positioning system) in the vertical direction, the integration of IMU(inertial measurement unit) with the GPS is not suitable for the vertical position estimation. This paper investigates an IMU-barometer integration for estimation of vertical position (as well as vertical velocity). In particular, a new two-step Kalman/complementary filter is proposed for accurate and efficient estimation using six-axis IMU and barometer signals. The two-step filter is composed of (i) a Kalman filter that estimates vertical acceleration via tilt orientation of the sensor using the IMU signals and (ii) a complementary filter that estimates vertical position using the barometer signal and the vertical acceleration from the first step. The estimation performance was evaluated against a reference optical motion capture system. In the experimental results, the averaged estimation error of the method was 19.7 cm while that of the raw barometer signal was 43.4 cm.

Index Terms—Vertical position, Vertical acceleration, Kalman filter, Complementary filter, IMU(inertial measurement unit), Barometer

1 Introduction

Accurate vertical position estimation for moving objects or humans is required in various fields. For example, in the control of an unmanned aerial vehicle (UAV) such as a drone, altitude may be considered as a kind of vertical displacement [1]. In sports such as skiing or snowboarding where the vertical displacement is severe, vertical displacement estimation using a portable sensor system can be analyzed to improve performance [2].

In order to overcome the limitations of most motion-capture systems in tracking trajectories of moving objects, fusion of GPS (Global Positioning System) and IMU (Inertial Measurement Unit) has been attempted. At this time, GPS provides displacement values that do not drift, and inertial sensors provide high sampling rates, so that high sampling rate and high accuracy displacement estimation are achieved through fusion of the two sensors. However, the error of vertical direction displacement of GPS is about 10 – 20m, which is much lower than that of horizontal displacement [3].

As an alternative to this, a barometer can be utilized for vertical displacement. However, a barometer is very noisy when used alone, because it estimates vertical displacement through the sensing of the atmospheric pressure change. It responds sensitively to atmospheric conditions, indoor / outdoor conditions, and even the degree of window opening, all of which cause errors in the calculation of vertical displacement. Thus, similar to IMU-GPS fusion, barometric-IMU convergence has been studied for high-sampling rate and high-accuracy vertical displacement estimation [2,4-7]. In particular, IMU-barometer fusion is used in pedestrian navigation [8] and fall detection [9], two varieties of human monitoring.

Two approaches to IMU / barometer fusion can be considered: tightly coupled and loosely coupled [5]. The tightly-coupled method is effective in modeling the noise of the two signals in a way that the signals of the IMU and the barometer are fused from the beginning of the filter, but the system matrix is large, as is the amount of computation required. The loosely-coupled method employs a two-step filter and is used more frequently because of convenience of application and efficiency of computation. In this approach, the two-stage filter computes the vertical displacement using (i) the first filter to calculate the attitude of the sensor using the IMU signal and obtain the vertical acceleration through it, and (ii) the second filter to fuse the vertical acceleration calculated from the barometer signal with the output of the previous filter.

Zihajehzadeh et al. [2] proposed a Kalman filter (KF) [10], which uses a six-axis IMU developed by the authors (i.e., a three-axis accelerometer and a three-axis gyroscope). Another Kalman filter, which sets the vertical displacement and the vertical velocity as state variables, was used as the second filter. Tanigawa et al. [7] applied the same Kalman filter as the first filter to the Xsens three-dimensional posture calculation based on a nine-axis IMU (i.e., six-axis IMU + three-axis geomagnetic sensor). Sabatini and Genovese [5] proposed an Extended Kalman Filter (EFK) that obtains quaternions using a six-axis IMU for the first filter and a complementary filter (CF) as the second filter. In the EKF proposed by Son and Oh [4], the IMU can be calibrated

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during measurement by adding the accelerometer bias and scale factor in addition to the vertical displacement and vertical velocity as state variables, thereby improving the accuracy of posture and vertical displacement estimation.

Among the above methods, all except [5] use a Kalman filter as the second filter, to exploit the Kalamn Filter's optimization and smoothing effects. However, the Kalman filter has a disadvantage that the computation required is larger than that of the complementary filter.

In this paper, a two-stage Kalman / complementary filter is proposed. Accurate vertical acceleration is estimated by using the tilt-estimation Kalman filter [10] adopted in [2] as the first filter. For the second filter, we propose a new combination IMU-barometric-based Kalman / complementary filter using the highly efficient complementary filter introduced in [11]. In addition, we examine (1) the effect of the accuracy of vertical-acceleration estimation on the accuracy of vertical-displacement estimation, and (2) the comparison between short and long endpoints and estimation accuracy based on the selection of complementary filter and Kalman filter in the second stage. In sum, we propose an optimal vertical displacement estimation filter that combines accuracy of estimation with computational efficiency.

2 Estimation Algorithm and Verification Experiment

2.1 Kalman filter for vertical acceleration estimation via posture estimation

The Kalman filter for vertical acceleration estimation, which is the first step, estimates the tilt as a vertical axis slope using the accelerometer and gyroscope signals from a six-axis IMU [10], and compensates for the gravitational acceleration component in the accelerometer signal (See Fig. 1).

The signals of the gyroscope (G) and the accelerometer (A) are modeled as follows:

$$\boldsymbol{s}_G = {}^S\boldsymbol{\omega} + \boldsymbol{n}_G \tag{1.a}$$

$$\boldsymbol{s}_A = {}^S\boldsymbol{g} + {}^S\boldsymbol{a} + \boldsymbol{n}_A \tag{1.b}$$

where $\boldsymbol{\omega}$ is the angular velocity, $\boldsymbol{a}$ is the sensor acceleration, and $\boldsymbol{n}$ is the measurement noise. The superscript S means that the vector is represented in the sensor coordinate system. In equation (1.b), the sensor acceleration is modeled as a first-order Markov process:

$$^S\boldsymbol{a}_t = c_a\, {}^S\boldsymbol{a}_{t-1} + \boldsymbol{\varepsilon}_{a,t} \tag{2}$$

where c_a and $\boldsymbol{\varepsilon}_{a,t}$ are a constant parameter and the time-varying error term of the acceleration model, respectively.

The first filter estimates the tilt attitude expressed by $^S\boldsymbol{Z}$ as a state vector, and obtains the vertical acceleration through the estimation. Here $^S\boldsymbol{Z}$ is a representation of the Z-axis unit vector of the inertial coordinate system (I) in the sensor coordinate system. It is part of a direction cosine matrix which is a three-dimensional attitude matrix. First, the process model that updates the state variable $x_1(= {}^S\boldsymbol{Z})$

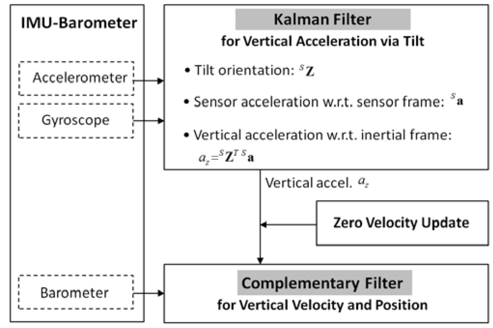

Fig. 1. Flowchart of the proposed two-step Kalman/complementary filter.

over time is expressed as follows from the strapdown integration associated with the angular velocity measurement of the gyroscope:

$$\boldsymbol{x}_{1,t} = {}^S\boldsymbol{Z}_t = (\boldsymbol{I} - \Delta t\tilde{\boldsymbol{s}}_{G,t-1})\, {}^S\boldsymbol{Z}_{t-1} + \Delta t(-\, {}^S\tilde{\boldsymbol{Z}}_{t-1})\boldsymbol{n}_G \tag{3}$$

Here, Δt is the sampling interval and the tilde (˜) denotes the outer matrix of the vector, e.g., $\tilde{a} = [a\times]$.

The measurement model is a mixture of accelerometer signal and sensor acceleration model as follows:

$$\boldsymbol{s}_{A,t} - c_a\, {}^S\boldsymbol{a}^+_{t-1} = g\, {}^S\boldsymbol{Z_t}\, {}^S\boldsymbol{a}^-_{\varepsilon,t} + \boldsymbol{n}_A \tag{4}$$

The following relations hold in the above equation: $^S\boldsymbol{g} = g\, {}^S\boldsymbol{Z}$, $^S\boldsymbol{a}^-_{\varepsilon,t} = {}^S\boldsymbol{a}^-_t - {}^S\boldsymbol{a}_t$, The superscripts $-$ and + mean the prior and the posterior, respectively.

From equations (3) and (4) we obtain the following KF equation:

$$\boldsymbol{x}_{1,t} = \boldsymbol{\Phi}_{t-1}\boldsymbol{x}_{1,t-1} + \boldsymbol{w}_{t-1} \tag{5.a}$$

$$\boldsymbol{z}_t = \boldsymbol{H}_t\boldsymbol{x}_{1,t-1} + \boldsymbol{v}_t \tag{5.b}$$

where the transition matrix $\boldsymbol{\Phi}_{t-1}$ is $I - \Delta t\tilde{\boldsymbol{s}}_{G,t-1}$; the process noise $\boldsymbol{w}_{t-1}$ is $\Delta t(-\, {}^S\tilde{\boldsymbol{Z}}_{t-1})\boldsymbol{n}_G$; the measurement vector $\boldsymbol{z}_t$ is $\boldsymbol{s}_{A,t} - c_a\, {}^S\boldsymbol{a}^+_{t-1}$; The observation matrix $\boldsymbol{H}_t$ is $g\boldsymbol{I}$; and the measurement noise $\boldsymbol{v}_t$ is $-\, {}^S\boldsymbol{a}_{\varepsilon,t} + \boldsymbol{n}_A$. The covariance matrix, $\boldsymbol{Q}_{t-1}$ (= $E[\boldsymbol{w}_{t-1} - \boldsymbol{w}^T_{t-1}]$) and $\boldsymbol{M}_t$ (= $E[\boldsymbol{v}_t\boldsymbol{v}^T_t]$) for the process noise and the measurement noise are as follows:

$$\boldsymbol{Q}_{t-1} = -\Delta t^2\, {}^S\tilde{\boldsymbol{Z}}_{t-1}\Sigma_G\, {}^S\tilde{\boldsymbol{Z}}_{t-1} \tag{6.a}$$

$$\boldsymbol{M}_t = \Sigma_{acc} + \Sigma_A \tag{6.b}$$

where E is the expectation operator, the covariance matrix Σ_G for gyro measurement noise is $\sigma^2_G I_3$; the covariance matrix Σ_A for accelerometer measurement noise is set to $\sigma_A \mathbf{I}_3$; and σ_G and σ_A are noise standard deviations. The covariance matrix Σ_{acc} of the acceleration model error defined by $E(({}^S\boldsymbol{a}^+_{\varepsilon,t})({}^S\boldsymbol{a}^+_{\varepsilon,t})^T)$ is set to $3^{-1}c^2_a||\, {}^S\boldsymbol{a}^+_{t-1}||\mathbf{I}$.

Once $^S\boldsymbol{Z}$ is obtained, the external acceleration $^S\boldsymbol{a}$ from the viewpoint of the sensor coordinate system is obtained as $\boldsymbol{s}_A - g\, {}^S\boldsymbol{Z}$, and finally the $\boldsymbol{Z}$-direction acceleration ^Ia_z from the viewpoint of the inertial coordinate system is obtained by the following equation:

$$a_z(= {}^Ia_z) = {}^S\boldsymbol{a}^T\, {}^S\boldsymbol{Z} \tag{7}$$

2.2 Complementary filter for vertical displacement estimation

In the second step, a complementary filter, the vertical displacement $h_z (= {}^I h_z)$ and the vertical velocity $v_z (= {}^I v_z)$ are estimated using the vertical acceleration transmitted through the first Kalman filter and the barometric signal.

The barometer pressure P can be converted to the vertical displacement h_z by the following equation [12].

$$h_z = 44330(1 - (P/P_0)^{0.19}) - h_{init} \tag{8}$$

where the unit of h_z is m(eters) and P_0 is the atmospheric pressure at sea level = 101,352 Pa(scals), and h_{init} is the altitude of the starting point of observation. In other words, h_z in this paper is the variation of the vertical displacement from the observation starting point. Also, in this paper, based on the highly transformed barometric pressure signal, the signal of the barometer (B) is modeled as

$$s_B = h_z + n_B \tag{9}$$

The state vector $\boldsymbol{x}_2$ in the second (complementary) filter is [11]:

$$\boldsymbol{x}_2 = [h_z v_z]^T \tag{10}$$

The complementary filter is applied as follows:

$$\boldsymbol{x}_{2,t} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \boldsymbol{x}_{2,t-1} + \begin{bmatrix} 1 & \Delta t/2 \\ 0 & 1 \end{bmatrix} \boldsymbol{K}_c \Delta t \times \varepsilon_{h,t-1} + \begin{bmatrix} \Delta t/2 \\ 1 \end{bmatrix} \Delta v_{z,t-1} \tag{11}$$

Here, ε_h is the difference between the barometric signal and the estimated value:

$$\varepsilon_{h,t-1} = s_{B,t-1} - h_{z,t-1} \tag{12}$$

and the velocity increment Δv_z is $\Delta t \times a_Z$. In addition, the complementary filter gain $\boldsymbol{K}_c$ is as follows:

$$\boldsymbol{K}_c = \begin{bmatrix} \sqrt{2(\sigma_{acc}/\sigma_B)} \\ \sigma_{acc}/\sigma_B \end{bmatrix} \tag{13}$$

where σ_{acc} and σ_B are the vertical acceleration estimate and the barometric signal, respectively. For reference, this complementary filter has low-pass filter characteristics of time constant $\tau = \sqrt{\sigma_B/\sigma_{acc}}$.

Prior to the above, the zero-velocity update (ZUPT) was applied. Based on the integration of noise, this is a technique to limit the drift error. When the zero speed is detected (as follows), the speed is set to zero instead of being set to the complementary filter integral from Eq. (11):

$$v_{z,t} = \begin{cases} 0, if(|a_{z,\tau}| < 0.1m/s^2 \forall_\tau \in [t - n\Delta t, t]) \\ Eq.(11)\ otherwise \end{cases} \tag{14}$$

where n is set to 12.

The overall configuration of the proposed two-stage Kalman / complementary filter is shown in Fig. 1.

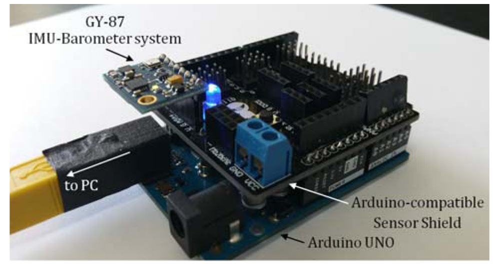

Fig. 2. GY-87 IMU-Barometer and Arduino board system.

2.3 Verification experiment

A GY-87 modular system was used for verification experiments. The GY-87 consists of a six-axis InvenSense MPU-6050 IMU (including accelerometer and gyro), a three-axis Honeywell HMC5883L geomagnetic sensor, and a Bosch BMP180 barometer, of which IMU and barometer were used for this experiment. (Refer to Table 1 for details.) The setup of the GY-87 is shown in Fig. 2 with an Arduino Uno R3 microcontroller and USB serial communication with the PC. The OptiTrack Flex13 optical motion capture system (NaturalPoint, Inc. USA) of Figure 3 was used as a ground-truth reference to obtain root mean square error (RMSE).

In addition to the proposed two-stage Kalman / complementary filter method, the following cases were compared and analyzed:

- The method of obtaining vertical acceleration:
  1) $a_{z,KF}$: the proposed method described in Section 2.1 using both accelerometer and gyroscope,
  2) $a_{z,OPT}$: a method of obtaining vertical acceleration using the highly accurate posture obtained from the Flex 13 camera system instead of the inertial sensor,
  3) $a_{z,app}$: Approximate method using only accelerometer [13]. That is, $a_{z,app} = ||s_A|| - g$.
- The method of obtaining vertical displacement:
  1) Using the complementary filter described in Section 2.2,
  2) [2] and [7] using Kalman filter.

Five experiments were conducted as follows. As shown in Fig. 3., Tests A to C were performed in an indoor gymnasium, elevated above the starting height by more than 3m. The optical marker was used only for the reference value corresponding to the vertical displacement (That is, $a_{z,OPT}$ was not obtained through the reference value of the sensor attitude.) For tests D and E on the other hand, the apparatus was lowered to within 1.5 m from the starting height. To confirm the influence of $a_{z,KF}$ and $a_{z,OPT}$ on the vertical displacement estimation, three additional markers were attached. The test movements were as follows:

- **Test A** Increased gradually from the starting height to around 3.5m. Waited for about 10 seconds before descending to the starting height again. During these upward and downward motions, the sensor was also tilted from side to side by at least 45 degrees. This experiment tested the influence of vertical acceleration

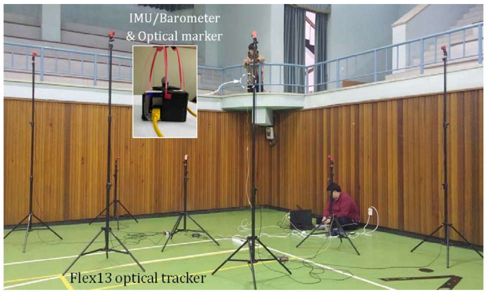

Fig. 3. Test setup with the Fex 13 optical motion capture system in an indoor gym.

$a_{z,KF}$ and attitude change $a_{z,app}$ on the estimation of vertical displacement.

- **Test B-C** Repeatedly ascending and descending by up to about 3m. Compared to Test B, Test C had faster and more frequent ups and downs. This experiment tested the influence of movement speed on vertical displacement estimation.
- **Test D** Cascaded steps up and down, then stop.
- **Test E** Observe the transition of the barometer signal at small altitude changes.

3 RESULTS

Table 2 shows the RMSE for each case, and Fig. 4 shows the result of applying the CF in the second step.

Test A - C results: effect of applying $a_{z,app}$. In cases of vertical motion in which the change of posture was not large (Test B or Test C), since $a_{z,app}$ maintains some accuracy, the vertical displacement estimate was also obtained more accurately than with the barometer by itself (s_B). However, in Test A, when the sensor posture changed significantly and vertical motion was performed, the estimation accuracy was even worse than the RMSE of s_B. The maximum error was 26.2 cm in Test C, and even less than 30 cm of accuracy was achieved in a displacement test of 3 m or more. In Test C, it seems that the influence of the large error of the barometer signal is reflected in the estimated value.

Test D - E results: Overall accuracy was highest for $a_{z,OPT}$, which estimated vertical displacement based on very accurate vertical acceleration. However, the proposed $a_{z,KF}$ method also showed very high accuracy, averaging 1.4 cm over $a_{z,OPT}$ method. The $a_{z,app}$ method showed very different results depending on the degree of sensor posture maintained. For example, in Test D, the RMSE was less than 20 cm for a motion that included a stationary state with no change in posture.

The barometer signal functions to prevent drift errors and ultimately determines the direction of the estimated value. In other words, it is inevitable that the estimated value is also affected if the error increases because of an abnormal barometer signal. For example, looking at the portion after 35 seconds in Test E, the sensor stopped at the 0 m initial position, but the barometer signal continued to drop, and you can see how the estimated value tracks it. Therefore, in order to improve estimation performance, it is necessary to improve the performance of the barometer itself.

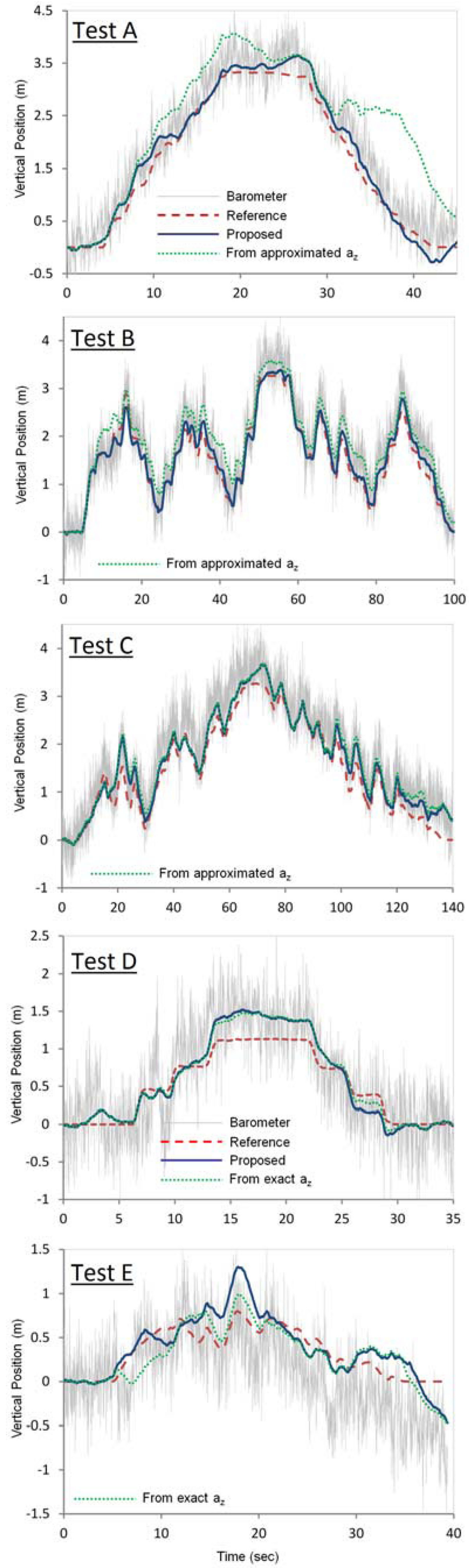

Fig. 4. Comparison of vertical position estimations.

In conclusion, there was no performance difference between CF and KF in all five tests. However, considering the amount of calculation (CF / KF calculation ratio = 12.5%), it can be concluded that CF is advantageous overall. The proposed method has an average RMSE of 19.7 cm, which is 55% better than the RMSE 43.4 cm of the barometer signal by itself. In [2], which estimated vertical acceleration with a Kalman filter and vertical displacement with a Kalman filter (i.e., a two-stage Kalman / Kalman filter), an average RMSE 27.4 cm was obtained.

4 Review and Discussion

In this paper, a two-stage Kalman / complementary filter for vertical displacement estimation based on IMU-barometer fusion was proposed. The first stage uses a Kalman filter (KF) to estimate vertical acceleration via the tilt posture of a six-axis IMU signal. The second stage uses a complementary filter (CF) to estimate vertical displacement and vertical velocity using vertical acceleration and a barometric signal transmitted through the first Kalman filter. The following conclusions are drawn from various experiments.

1. In the vertical displacement estimation filter using the vertical acceleration estimate and the barometric signal, there was almost no difference in accuracy between KF and CF (absolute difference value average 0.15 cm). However, considering the calculation time, the CF method is eight times faster than KF so we conclude that the CF adopted by this paper is better.

2. Unless there is little change in attitude, approximated vertical acceleration estimation using only an accelerometer is inadequate for use in estimating vertical displacement (despite the ease of sensor configuration and method).

3. In the vertical acceleration estimation based on the IMU-barometric fusion sensor, the performance of the barometer has a great influence on the estimation accuracy, and it seems that there is a limit to improving the accuracy through the IMU. However, in comparison with the barometer signal error of 43.4cm average RMSE, the average RMSE error of the proposed method was 19.7cm.

The method proposed in this paper – efficiently improving the accuracy of vertical displacement estimation through IMU-barometric fusion – can be widely applied to sports science and ship VDR (voyage data recording), as well as pedestrian navigation and fall detection.

TABLE 1
Specification of GYU-87 IMU-Barometer system.

	Accelerometer	Gyroscope	Barometer
Model	Invensense MPU-6050	Invensense MPU-6050	Bosch BMP 180
Full-Scale Range	$\pm 2 \sim 16g$	$\pm 250 \sim$ 2000 deg/s	$\pm 300 \sim$ 1100 hPa
Sensitivity	0.000061 $\sim$ 0.0049 g	0.0076 $\sim$ 0.061 deg/s	0.0015 hPa
Max. Sampling Rate	1000 Hz	8000 Hz	128 Hz
Digital Resolution	16 bit	16 bit	19 bit

TABLE 2
RMSE (root mean squared error) of raw barometer signal and estimations of each case (unit: cm)

Test	S_B	**Filter**	$a_{z,OPT}$	$a_{z,KF}$	$a_{z,app}$
Test A	41.7	CF	N/A	19.9	86.8
		KF	N/A	19.8	86.9
Test B	42.0	CF	N/A	13.9	37.4
		KF	N/A	13.8	37.4
Test C	50.4	CF	N/A	26.2	32.4
		KF	N/A	26.2	32.4
Test D	40.8	CF	16.8	18.5	18.2
		KF	16.3	18.1	18.6
Test E	42.2	CF	18.7	19.9	32.1
		KF	18.7	19.8	32.0
Average	43.4		17.8	19.7	41.4
			17.5	19.5	41.5

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