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A miniaturized attitude estimation system for a gesture-based input device with fuzzy logic approach

Wook Chang, Jing Yang, Eun-Seok Choi, Won-Chul Bang, Kyoung-Ho Kang,
Sung-Jung Cho and Dong-Yoon Kim
Samsung Advanced Institute of Technology
Mt. 14-1, Nongseo-Ri, Giheung-eup, Yongin-si
Gyeonggi-do, Korea 449-712
Email: {wook.chang, jing.yang, eunseok.choi, wc.bang, kyoungho.kang, sung-jung.cho, kdy2891}@samsung.com

***Abstract*—In this paper, we develop an input device equipped with accelerometers and gyroscopes. The installed sensors measure the inertial measurements, i.e., accelerations and angular rates produced by the movement of the system when a user is writing on the plane surface or in the three dimensional space. The gyroscope measurement are integrated once to give the attitude of the system and consequently used to remove the gravity included in the acceleration measurements. The compensated accelerations are doubly integrated to yield the position of the system. Due to the integration processes involved in recovering the users' motions, the accuracy of the position estimation significantly deteriorates with time. Among various error sources of the system incorrect estimation of attitude causes the largest portion of the positioning error since the gravity is not fully cancelled. In order to solve this problem, we propose a Kalman filter-based attitude estimation algorithm which fuses measurement data from accelerometers and gyroscopes by fuzzy logic approach. In addition, the online calibration of the gyroscope biases are performed in parallel with the attitude estimation to give more accurate attitude estimation. The effectiveness and the feasibility of the presented system is demonstrated through computer simulations and actual experiments.**

I. Introduction

Due to the rapid development of small-sized digital devices, there have been great interests in the development of comfortable and easy-to-use input devices.

Among various approaches to achieve the goal, the idea of building input devices using inertial measurement unit such as accelerometers and gyroscopes has long been investigated and reported in the research papers or patents. Since inertial measurements are not affected by external signal jamming or magnetic field and need no external reference sources, the system can be used as a totally self-contained input device. The application of inertial input devices covers signature verification [1], cursor pointing [2], handwriting recovery [3], and virtual/augmented reality [4].

In order to recover the perfect three dimensional information of a moving object in the free space, 6 degree-of-freedom (DOF) inertial measurements, i.e., three axes accelerations and three axes angular rates are required which is well known in the field of inertial navigation. Since the inertial navigation system (INS) requires several integration processes to obtain position information which causes large positioning error with time, most commercial INSs use the external reference sources such as global positioning system (GPS) information to compensate INS errors [5]. For the presented input device, however, it is not a feasible solution to use external reference sources due to its size, battery, etc.

In this paper, we propose a method to make a commercially feasible inertial input device with INS theory. Especially, the estimation algorithm of roll and pitch angles is investigated since those information largely affect the accuracy of the position estimation. For this purpose, we apply the fuzzy Kalman filter approach to give robust and accurate attitude estimator by fusing inertial data.

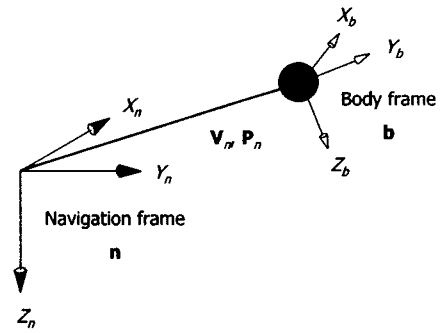

Fig. 1. The navigation coordinate frame n and the body coordinate frame b are shown to describe the position of a pen system

II. Inertial Navigation Systems

In our system, the following assumptions are made:

1) The influence of the rotation of the Earth is neglected.
2) The Earth is regarded as a plane.
3) The gravity vector is a constant, i. e., $G = [0\ 0\ 9.8]^\top\ (m/s^2)$.

Fig 1 illustrates an object shown in two coordinate frames. The accelerometers and gyroscopes rigidly installed on the object and measure the accelerations and angular rates resolved along the axes of the object. In order to calculate the relative position of the object in the free-space (where the coordinate of the free-space is called inertial frame), the acceleration measurements shown in the body frame should be transformed to those shown in the navigation frame. The navigation frame n represented by the orthogonal axes X_n, Y_n, and Z_n is the coordinate frame with respect to which the location of the pen needs to be estimated. The body frame b is attached to the pen and is aligned with axes of the inertial measurement unit (IMU). The measurements of the IMU are the specific force, i. e., acceleration $f_b = [f_{bx}\ f_{by}\ f_{bz}]^\top$ and angular rate $\omega_b = [\omega_{bx}\ \omega_{by}\ \omega_{bz}]^\top$ in the body frame b. Position of the object $P_n = [P_x\ P_y\ P_z]^\top$ is the position vector of the origin of frame b in the navigation frame and velocity of the object $V_n = [V_x\ V_y\ V_z]^\top$ is the rate of change of P_n. The attitude of the vehicle $E = (\phi,\ \theta,\ \psi)$ is represented by the three Euler angles, yaw (ψ), pitch (θ), and roll (ϕ), where the order of rotation is about b_z followed by b_y and then b_x. This results in a rotation matrix describing the orientation of frame b with respect to the navigation frame n

The state-space equations governing the overall system are

$$\dot{P}_n = V_n \tag{1}$$

$$\dot{V}_n = C_b^n f_b - G \tag{2}$$

$$\dot{\phi} = \omega_{bx} + (\omega_{by} \sin\phi + \omega_{bz} \cos\phi) \tan\theta \tag{3}$$

$$\dot{\theta} = \omega_{by} \cos\phi - \omega_{bz} \sin\phi \tag{4}$$

$$\dot{\psi} = \frac{\omega_{by} \sin\phi + \omega_{bz} \cos\phi}{\cos\theta} \tag{5}$$

where C_b^n is the direction cosine matrix whose definition can be found in [6].

III. Estimation of roll and pitch angles

Three integration steps are involved to obtain the final position of the system in the free space. Angular rates are integrated once to give the Euler angles by which the acceleration measurements are compensated. The compensated acceleration measurements are integrated twice to give the position. Therefore, the positional error growth due to the attitude estimation will be roughly proportional to t^3. Since the accelerations due to the users' handwriting motion seldom exceed $2g$, small errors in the attitude estimation will lead to large errors. Therefore, the accurate estimation of the attitude is crucial for the presented system.

Among three Euler angles, the roll and pitch angles play major role to remove the effect of gravity in the transformed acceleration in the navigation frame. Angular rate measurements are used to compute the Euler angles. But the main drawback of using angular rate sensors is the unbounded growth of angular error with time due to the integration process involved. However, it should be noted that the short term accuracy of angular rate sensors are quite acceptable.

On the other hand, the accelerometers can be used to estimate the roll and pitch angles of the system without the unbounded growth of errors. However, the signals of accelerometers have high-frequency noise and are very susceptible to the dynamic motion of the system, which in turn makes the calculated angles less reliable when the system is in dynamic state.

By synergetically blending two different types of signals, one can obtain more accurate Euler angles [5], [7], [8].

A. Complementary filter

Let us consider the following simple discrete-time linear system

$$x(kT+T) = Gx(kT) + \omega(kT),\ \tilde{y}(kT) = Cx(kT) + \nu(kT) \tag{6}$$

where $x \in R^n$ is the state vector, $\tilde{y} \in R^p$ is the measurement, $A \in R^{n\times n}$, $C \in R^{p\times n}$, $\omega \in R^n$ is the process noise, and $\nu \in R^p$ is the measurement noise.

A discrete-time Kalman filter recursively computes the estimate $\hat{x}$ of the state vector which is optimal linear minimum variance estimation.

For the above system, a version of Kalman filter algorithm can be described as follows:

$$\begin{aligned} K(kT) &= P^-(kT)C(kT)^\top \ R + C(kT)P(kT)^{-1}C(kT)^\top \ ^{-1} \\ \hat{x}(kT) &= \hat{x}^-(kT) + K(kT)\left(\tilde{y}(kT) - \hat{y}(kT)\right) \\ P(kT) &= \left(I - K(kT)C(kT)\right)P(kT)^- \\ \hat{x}^-(kT+T) &= G\hat{x}(kT) \\ P^-(kT+T) &= GP(kT)G^\top + Q \end{aligned} \tag{7}$$

where $\hat{y}(kT) = C\hat{x}(kT)$, Q and R are noise covariance matrices.

The Kalman filter is popular for INS since it can blend data from different navigation sensors with noisy measurements to estimate the true navigation data. Various Kalman filtering algorithm has been presented in the literature [5]–[8]. In this paper, we adopt complementary filter approach with feedback implementation, in which Kalman filter estimates only error states.

Let us introduce the nonlinear differential equations for roll and pitch angles:

$$\dot{x} = f(x,u) + \omega \tag{8}$$

where $x = [\phi\ \theta]^\top$, $u = [\omega_{bx}\ \omega_{by}\ \omega_{bz}]^\top$, and $f(x,u) = [\omega_{bx} + (\omega_{by}\sin\phi + \omega_{bz}\cos\phi)\tan\theta\ \ \omega_{by}\cos\phi - \omega_{bz}\sin\phi]^\top$.

In the case of sufficiently low acceleration, the accelerometer signals can be served as an alternative source of estimating roll and pitch angles. For this case, the specific force applied to the system is related to roll and pitch angles as follows

$$\tilde{y} = x + \nu \tag{9}$$

where $\tilde{y} = [\tilde{\phi}\ \tilde{\theta}]^\top = \ \arctan(-\tilde{f}_{by}, -\tilde{f}_{bz})\ \arctan\ \tilde{f}_{bx}, \sqrt{\tilde{f}_{by}^2, \tilde{f}_{bz}^2}\ \ ^\top$.

In order to apply the linear Kalman filter (7) to the nonlinear system (8), we utilize extended Kalman filter (EKF) approach. It should be noted that only the error states are estimated with EKF. Due to the page limitation, only the final system model to apply the Kalman filter is shown as follows:

$$\begin{aligned} \delta x_a(kT+T) &= G_a(kT)\delta x_a(kT) + \omega_a(kT) \\ \delta y(kT) &= \tilde{y} - \hat{y} = C_a \delta x_a(kT) + \nu(kT) \end{aligned} \tag{10}$$

where $\delta x_a = [\delta\phi\ \delta\theta\ \delta\omega_{bx}\ \delta\omega_{by}\ \delta\omega_{bz}]^\top$, ω_a and ν are white noise vectors, and $G_a(kT) = \exp(A_a T)$, $C_a = [I_{2\times 2}\ 0_{2\times 3}]$, $\hat{y} = \hat{x} = [\hat{\phi}\ \hat{\theta}]^\top$, $\dot{\hat{x}} = f(\hat{x}, \tilde{u})$, $\tilde{u}$ is measured angular rates, and $A_a = \begin{bmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial u} \\ 0_{3\times 2} & 0_{3\times 3} \end{bmatrix}$

Consequently, the complementary filter approach under the low acceleration is summarized as follows:

1) Initialize Kalman filter
2) Calculate the estimation of roll $\hat{\phi}$ and pitch $\hat{\theta}$ using (8)
3) Calculate the estimation of errors $\delta\hat{x}_a$ by applying Kalman filter algorithm in (7) to the system in (10).
4) Feed the error state estimates to the attitude estimator by updating $\hat{\phi}$ and $\hat{\theta}$ with $\hat{\phi} := \hat{\phi} + \delta\hat{\phi}$ and $\hat{\theta} := \hat{\theta} + \delta\hat{\theta}$
5) Reset the error states of the Kalman filter to zero
6) Go to step 1

B. Fuzzy blending

When the system experiences high acceleration due to significant change in speed or attitude, the estimated roll and pitch angles by Kalman filter become unreliable. During such intervals, the angular rate signals alone should be adopted to calculate the roll and pitch angles. In this case, the Kalman filter algorithm in (7) is simply reduced to

$$\begin{aligned} \hat{x}(kT) &= \hat{x}^-(kT) \\ P(kT) &= P(kT)^- \\ \hat{x}^-(kT+T) &= G\hat{x}(kT) \\ P^-(kT+T) &= GP(kT)G^\top + Q \end{aligned} \tag{11}$$

The estimation algorithm combining (7) and (11) is as follows [5]:

$$\begin{aligned} K(kT) &= \sigma(kT)P^-(kT)C(kT)^\top \times \\ &\quad R + C(kT)P(kT)^{-1}C(kT)^\top \ ^{-1} \\ \hat{x}(kT) &= \hat{x}^-(kT) + \sigma(kT)K(kT)\left(\tilde{y}(kT) - \hat{y}(kT)\right) \\ P(kT) &= \left(I - \sigma(kT)K(kT)C(kT)\right)P(kT)^- \\ \hat{x}^-(kT+T) &= G\hat{x}(kT) \\ P^-(kT+T) &= GP(kT)G^\top + Q \end{aligned} \tag{12}$$

where $\sigma(kT) = 1$ for low acceleration and $\sigma(kT) = 0$ for high acceleration.

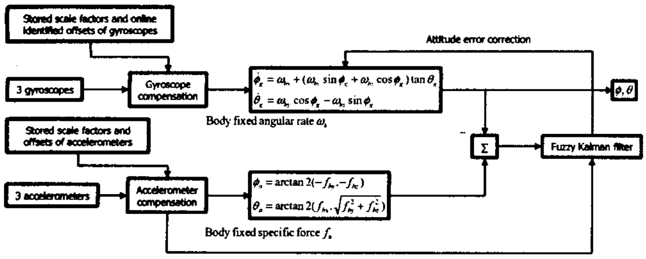

Fig. 2. Attitude estimator

Therefore, some intelligent algorithm to detect the period of high acceleration is required. In [5], [8], [9], various types of acceleration or motion detection algorithms have been proposed. Simply speaking, the acceleration detection can be performed by observing the acceleration measurements. If the acceleration measurements are zero, then the system can be determined in the static state. However, it should be noted that the acceleration measurements can be zero despite of dynamic state. In order to avoid the wrong detection result, the above-mentioned works investigate signals from sensor for a predefined period of time to determine if the system is moving or not. This approach, however, may miss samples of motion and give wrong initial condition for the attitude estimator.

The idea to resolve this problem is to utilize fuzzy inference system which is described with following fuzzy rules:

$$\begin{array}{l} \text{IF } |f_b| - 9.8 \text{ is ZERO THEN } \sigma \text{ is } 1 \\ \text{IF } |f_b| - 9.8 \text{ is NOT ZERO THEN } \sigma \text{ is } 0 \end{array} \tag{13}$$

where the triangular fuzzy membership function $\text{ZERO}(x) = \max(\min(\frac{x-a}{b-a}, \frac{c-a}{c-b}), 0)$, a and c denote the left and right feet of the triangle, c is the center of the triangle, and $\text{NOT ZERO}(x) = 1 - \text{ZERO}(x)$.

Combining fuzzy inference system (13) with the Kalman filter gives fuzzy Kalman filter which can give more robust and accurate attitude estimator. In addition, we use the simple moving average filter to identify biases of the gyroscopes online.

Fig. 2 illustrates the structure of data flow of the proposed attitude estimator.

IV. Reproduction of User's Motion

Based on the results from the previous sections, we are now in the position of actual processing of user's motion. Here, we will introduce only the summary of this process due to the page limitation. Interesting readers can refer to the cited references.

Overall algorithm

1) Determine if the user begins the motion by checking a button. If the button is pushed, go to step 2. Otherwise repeat step 1.
2) Get inertial measurements f_b and ω_b from accelerometers and gyroscopes.
3) Calculate roll and pitch angles with the proposed algorithm detailed in Section III.
4) Find INS solution with (1), (2) and (5).
5) Store measurements and calculated values.
6) Determine if the user finishes the motion by checking the button. If the button is released, go to step 7. Otherwise go to step 2.
7) Based on the stored data, find the meaningful segments of the user's motion [9].
8) Compensate the solutions obtained in step 4 by applying zero velocity compensation (ZVC) [9]–[11] to each segment.
9) Transform the three-dimensional motion data into the two-dimensional motion data [9].
10) Transfer the two-dimensional data obtained in step 9 to a recognition module and go to step 1.

TABLE I

ACCELEROMETER ERROR PARAMETERS FOR THE SIMULATION

Axis	Accelerometer		
	Noise ω_{f_b} (STD)	Offset δb_{f_b} (m/s^2)	Scale factor δK_{f_b} (m/s^2)
x	0.02	0.02	0.051 $\times 10^{-2}$
y	0.0239	0.0239	0.061 $\times 10^{-2}$
z	0.02	0.02	0.051 $\times 10^{-2}$

TABLE II

GYROSCOPE ERROR PARAMETERS FOR THE SIMULATION

Axis	Gyroscope		
	Noise ω_{ω_b} (STD)	Offset δb_{ω_b} (rad)	Scale factor δK_{ω_b} (rad)
x	0.0093	0.0468	0.4469 $\times 10^{-2}$
y	0.0099	0.0042	0.00401 $\times 10^{-2}$
z	0.0093	0.0468	0.44692 $\times 10^{-2}$

V. Simulation Example

In this section, simulation results to verify the performance of the proposed attitude estimation algorithm are provided. The sampling period $T_s = 0.01$ (sec), the initial value of the error covariance matrix $P(0) = I_{5\times5}$ and noise covariance matrices are $Q = 10I_{5\times5}$ and $R = I_{2\times2}$, respectively. For the fuzzy inference system, the parameters of the membership function ZERO are $a = -0.0197$, $b = 0$, and $c = 0.0197$. In order to mimic the realistic situation, various error sources are added during the simulation, which are summarized in Table I and Table II. The measurement signals for the simulation are generated by

$$\tilde{f}_b = (1-\delta K_{f_b})f_b - \delta b_{f_b} - \omega_{f_b}, \; \tilde{\omega}_b = (1-\delta K_{\omega_b})\omega_b - \delta b_{\omega_b} - \omega_{\omega_b} \tag{14}$$

To explicitly show the effect of the proposed method, we compare the Monte Carlo simulation results of the proposed algorithm with those of gyroscope-based method and switching method. In the switching method, the estimated roll and pitch angles by the accelerometers and gyroscopes are simply switched based on predefined switching mechanism presented in [10]. Fig. 3 show the simulation results.

Root mean of squared error (RMSE) of the roll angle of the proposed method is 0.002252 (rad) while those of the gyroscope-based method and switching method are 0.088291 (rad) and 0.002856 (rad), respectively. For pitch angle, RMSEs are obtained as 0.002321 (rad), 0.002975 (rad), and 0.002827 (rad) for the proposed method, gyroscope-based method, and the switching method, respectively. The result clearly shows the improvement of the performance of the attitude estimator by the proposed scheme.

VI. Real Experiments

This section presents the results of real experiments on writing in the space. The sensor configuration of the implemented system used in the experimental work is fitted with the followings. Details of the sensor configuration can be found in [9], [10].

- A Kionix dual axis accelerometer (KX120-L20) with range of $\pm 2g$, sensitivity of 1000 mV/g and $2.5V$ of zero g offset

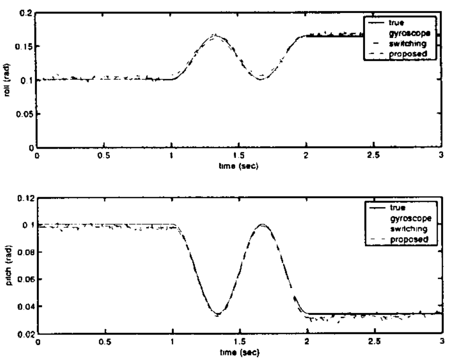

Fig. 3. The roll and pitch angles of the gyroscope-based method (dotted line), the switching method (dash dotted line), and the proposed method (dotted line)

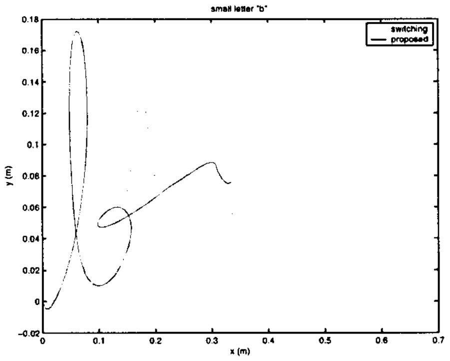

Fig. 4. Recovered result of the small letter "b"

voltage for the measurement of the specific forces resolved along the x and y axes of the system.

- A Kionix single axis accelerometer (KXF00-L20) with range of $\pm 2g$, sensitivity of $1000mV/g$ and $2.5V$ of zero g offset voltage for the measurement of the specific force resolved along the z axis of the system.
- Two single axis gyroscope (Murata ENC-03M) with range of $\pm 300deg/sec$, sensitivity of $0.67mV/deg/sec$ and offset voltage $1.35V$ for the measurement of angular velocities along the x and z axes.
- A single axis gyroscope (ADI ADXRS300AQC) with range of $\pm 300deg/sec$, sensitivity of $5mV/deg/sec$ and offset voltage $2.5V$ for the measurement of angular velocity along the y axis.

Here, we will show the final recovered trajectory of the user's motion using the algorithm proposed in Section IV. However, the final recovered results can show the performance improvement due to the proposed attitude estimator indirectly. In addition, we omit the quantitative verification process of the recovered results since one can identify the improvement of the final results intuitively. Fig. 4 shows some exemplary results of the presented gesture-based input device employing the proposed attitude estimation algorithm, which clearly shows the effectiveness of the proposed algorithm.

VII. Conclusions

In this paper, we have presented an input device using inertial sensors. The signals from gyroscopes are integrated once to give the attitude of the system and consequently used to remove the gravity included in the acceleration signals. The compensated accelerations are integrated twice to yield the position of the system. During the motion recovery process, Kalman filter approach is adopted to estimate the roll and pitch angles which are crucial in the position estimation. In order to improve the performance of the attitude estimator, the traditional Kalman filter is slightly modified to be used with a fuzzy inference system. In the simulation, we have generated realistic inertial measurements to which the proposed algorithm has been applied. The simulation results have shown the the proposed method is effective for better estimation result of roll and pitch angles. In the real experiment, the effect of the proposed algorithm has been indirectly shown with the final recovered trajectory of a user's motion.

References

[1] R. Baron and R. Plamondon, "Acceleration measurement with an instrument pen for signature verification and handwriting analysis," *IEEE Transactions on Instrumentation and Measurement*, vol. 38, no. 6, pp. 1132–1138, Dec. 1989.

[2] S. Lee, G. J. Nam, J. Chae, H. Kim, and A. J. Drake, "Two-dimensional position detection systems with MEMS accelerometer for mouse applications," in *Proceedings of the 38th Design Automation Conference*, June 2001, pp. 852–857.

[3] T. Miyagawa, Y. Yonezawa, K. Itoh, and M. Hashimoto, "Handwritten pattern reproduction using 3d inertial measurement of handwriting movement," *Transactions of the Society of Instrument and Control Engineers*, vol. 38, Jan. 2002.

[4] A. D. Cheok, K. G. Kumar, and S. Prince, "Micro-accelerometer based hardware interfaces for wearable computer mixed reality applications," in *Proceedings of ISWC2002*, 2002.

[5] H. Rehbinder and X. Hu, "Drift-free attitude estimation by fusion of inertial data," in *Proceedings of the 2001 IEEE International Conference on Robotics and Automation*, Seoul, Korea, May 2001, pp. 4244–4249.

[6] G. Dissanayake, S. Sukkarieh, and H. Durrant-Whyte, "The aiding of a low-cost strapdown inertial measurement unit using vehicle model constraints for land vehicle applications," *IEEE Transactions on Robotics and Automation*, vol. 17, pp. 731–747, Oct. 2001.

[7] G. Grenon, P. E. An, S. M. Smith, and A. J. Healy, "Enhancement of the inertial navigation system for the Morpheus autonomous under water vehicles," *IEEE Journal of Oceanic Engineering*, vol. 26, pp. 548–560, Oct. 2001.

[8] E. Foxlin, "Inertial head-tracker sensor fusion complementary separate bias kalman filter," in *Proceedings of VRAIS'96*, 1996, pp. 185–195.

[9] W.-C. Bang, W. Chang, K.-H. Kang, E.-S. Choi, A. Potanin, and D.-Y. Kim, "Self-contained spatial input device for wearable computers," in *Proceedings of 7th IEEE International Symposium on Wearable Computers*, Oct. 2003, (To be published).

[10] W. Chang, K. H. Kang, E.-S. Choi, W.-C. Bang, A. Potanin, and D.-Y. Kim, "Design of a pen-shpaed input device usng the low-cost inertial measurement unit," *Journal of Korea Fuzzy Logic and Intelligent Systems Society*, vol. 13, no. 2, pp. 247–258, 2003.

[11] W. Chang, K.-H. Kang, E.-S. Choi, A. Potanin, W.-C. Bang, and D.-Y. Kim, "Development of a pen-type input device using miniaturized inertial sensors," in *Proceedings of HCI2003*, Feb. 2003.