In Use Parameter Estimation of Inertial Sensors by Detecting Multilevel Quasi-static States

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Abstract. We present an autoadaptive algorithm for in-use parameter estimation of MEMS inertial accelerometers and gyros[1] using multi-level quasi-static states for greater accuracy and reliability. Multi-level quasi-static states are detected robustly using data from both gyros and accelerometers. Proper estimation of time-varying sensor parameters allows us to develop a mixed-reality real-time hand-held orientation tracker with dynamic accuracy of less than 2^0. Existing methods like Kalman filters do not take time-varying nature of parameters into account, instead modelling the time-variation as higher values in noise covariance matrices; thus underestimating the sensor capabilities.

1 Introduction

Micro-Electro-Mechanical System (MEMS) based inertial accelerometers and gyros are used in a wide range of applications such as human motion tracking [1] and surgical applications [2] because of their low cost, small size and *sourceless* [3] nature. Veltink *et al.* [4] used uni-axial accelerometers for detecting static and dynamic activities. Detecting levels of activity has been used in many applications like rehabilitation treatment of patients [4] and activity monitoring.

However, accelerometer and gyro based devices suffer from substantial drift due to time-varying nature of bias and other parameters. Recent research has focused on integrating multisensor signals of gyros and accelerometers to estimate orientation [1],[8] using Kalman filters. However, Kalman filtering has a serious drawback of high computational cost, which is unacceptable in some applications that require real-time output or are computationally constrained. Furthermore,

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[1] Gyro stands for gyroscopes, gyrometers, angular rate sensors used in different texts

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performance of Kalman filters depend critically on estimating a large number of modelling parameters. Failing to capture the time-varying nature of parameters, they instead overestimate the noise covariance matrices. To capture the time-varying nature of bias, Foxlin [8] used bias values as a part of the state vector of the Kalman filter. In such an algorithm, bias values are re-estimated at every sample, which is inefficient; because bias of the gyro changes slowly and there is no need to re-estimate it so frequently.

We propose a new autoadaptive method to re-estimate and update the sensor parameters while in use, by detecting multi-level quasi-static states for use in a mixed-reality orientation tracking device. We combine data from both tri-axial accelerometers and gyros to robustly detect multi-level quasi-static states, providing the accuracy and reliability needed for its use in parameter estimation, which was not possible by using uni-axial accelerometers alone.

Accurate parameter estimation using multi-level quasi-static states allows the development of a real-time handheld orientation tracker for a mixed reality device used in HMDs (Head Mounted Displays) [1], surgical applications and other applications [10], [11]. The basic goal of this algorithm is to allow the system to automatically adjust to variations in external conditions and sensor parameters. In this work, we present a method of processing signals from tri-axial gyros, accelerometers, and magnetometers to obtain a drift-less and accurate estimate of orientation that is not possible with gyros, accelerometers or magnetometers alone. Bachmann *et al.* [3] has used tri-axial accelerometers as inclinometers on the assumption that magnitude of the kinematic linear acceleration is negligible in comparison to gravity. In this paper, we show that re-estimating the bias in quasi-static states is good enough for accurate orientation tracking. Results of the orientation tracking in a hand-held instrument are also discussed.

2 Modelling of Sensors

We use a sensor model similar to that described in [5]:

$$\mathbf{u_g} = \mathbf{K_g} \cdot \mathbf{R_g} \cdot \boldsymbol{\omega}_\mathbf{s} + \mathbf{b_g} \tag{1}$$

$$\mathbf{u_a} = \mathbf{K_a} \cdot \mathbf{R_a} \cdot \mathbf{a_s} + \mathbf{b_a} \tag{2}$$

$$\mathbf{u_m} = \mathbf{K_m} \cdot \mathbf{R_m} \cdot \mathbf{h_s} + \mathbf{b_m} \tag{3}$$

where $\boldsymbol{K_g}$ is the diagonal matrix for gyro gain, $\boldsymbol{\omega_s}$ is the angular velocity in cartesian coordinates, $\boldsymbol{b_g}$ is the bias, $\boldsymbol{R_g}$ is orientation matrix to convert each sensor output to a single cartesian coordinate system, compensating errors due to misalignment. Similar convention follows for accelerometers (eq. (2)) and magnetometers (eq. (3)) respectively.

3 Calibration

3.1 Pre-calibration

Pre-calibration of the sensors is performed once, while manufacturing the device similar to the method described by Ferraris [5], and estimates the sensor parameters listed in Sect. 2. The bias and gain of gyros and accelerometers ($\boldsymbol{b_g}$, $\boldsymbol{K_g}$, $\boldsymbol{b_a}$, $\boldsymbol{K_a}$) vary with time from the pre-calibrated values because of temperature and other random factors.

3.2 Detecting Quasi-static States

We propose a novel fuzzy algorithm to detect quasi-static states. These states are detected when the sensor signals are changing insignificantly over time. A constant acceleration or an exact cancellation of acceleration is unlikely to happen with typical hand movements [6] because of the physiological constraints, therefore a quasi-static state is a good indicator of the object being at rest. During the static state, the white gaussian noise N_s, for L samples in each of the sensor signals can be estimated (during start-up calibration) as:

$$N_s = \sum_{i=1}^{L} \frac{s^2[i]}{L} \tag{4}$$

where $s[i]$ is the sensor signal. If the estimated noise is $\left[N_{gx}, N_{gy}, N_{gz}\right]$ for gyros and $\left[N_{ax}, N_{ay}, N_{az}\right]$ for accelerometers, then the decision rule for static state is:

$$\gamma[j] = \frac{1}{6}\left(\frac{1}{s_{ge}^2} \sum_{q=x,y,z} \frac{s_{gq}^2[j]}{N_{gq}} + \frac{1}{s_{ae}^2} \sum_{q=x,y,z} \frac{s_{aq}^2[j]}{N_{aq}}\right) \tag{5}$$

where s_{ge} and s_{ae} is the expected RMS value of signal during normal device use (for example for gyro it is $60^0/sec$ and $1m/s^2$ for accelerometers). Then γ is low pass filtered (LPF) to get $\boldsymbol{\gamma_L}$. This ensures that the static state is of a minimum duration.

$$\boldsymbol{\gamma_L}[i] = LPF\{\gamma[i]\} \tag{6}$$

If $\boldsymbol{\gamma_L}[i] <$ threshold, which can be determined experimentally or dynamically adjusted with a learning algorithm, then it is a quasi-static state. Using multiple threshold levels, we can detect different levels of static states and make a high-level decision for the amount of correction to be made in the parameters. Fig. 1 shows the performance of the quasi-static state detector (with only one sensor signal shown). The graph demonstrates that even when variation in a single sensor is low, other sensors help make an accurate decision for a static state.

3.3 In Use Calibration of Gyros and Accelerometers

In quasi-static state, the calibrated output $\boldsymbol{\omega_s}$ ideally should be zero. However, it is not zero because of the time-varying nature of the bias. The change in bias $\Delta\boldsymbol{b_g}$ is estimated during quasi-static state, and the bias parameter is updated as

$$\boldsymbol{b_g^{new}} = \boldsymbol{b_g} - \Delta\boldsymbol{b_g} \tag{7}$$

The parameters for the accelerometer, like sensitivity and bias, are also re-estimated in static state, similar to the method described in [6].

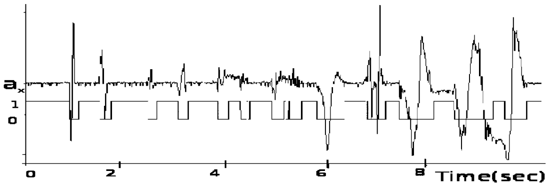


Fig. 1. Output of Quasi-Static State detector shown with x-axis acceleration along with digital static state graph. Digital 1 means quasi-static while 0 means not. The detector detects static states robustly because it combines information from all the sensors

4 Orientation Estimate Using Multi-level Quasi-static States

4.1 Algorithm

Block diagram of the system for estimating the orientation is shown in Fig. 2. The sensor data is calibrated and processed to get orientation and acceleration in the body frame. We define two levels of static state: (A) *Quasi-Static*: when device is almost static, and (B) *Semi-Static*: when the device is moving very slowly, detected as described in Sect. 3.2. In the quasi-static state, we re-calibrate the sensors as described in Sect. 3.3, and in semi-static state we correct the orientation for drift using information from accelerometers and magnetometers.

In our ongoing research, we are developing algorithms to determine position from accelerometers. This involves obtaining kinematic linear acceleration (acceleration without gravity). Since accelerometers measure acceleration plus gravity, orientation information is needed to subtract gravity vector from the acceleration signals. An error of $\delta\theta$ results in an error of $g \sin \delta\theta$ in the acceleration components, creating a false horizontal acceleration in the output of the inertial navigator [1], making position error unbounded because of double integration involved in the filters. Therefore accurate estimation of orientation is essential.

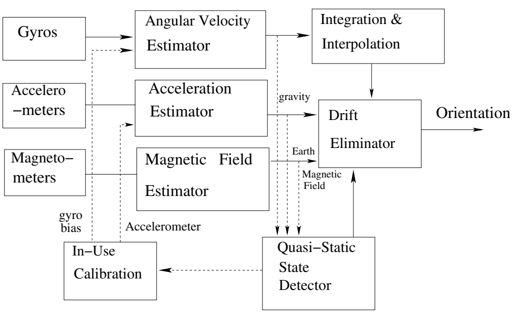


Fig. 2. Block diagram for calculating orientation. *Static-State Detector* signals the *In-Use Calibrator* to re-estimate parameters, and *Drift Eliminator* to correct for gyro drifts using information from accelerometers and magnetometers

4.2 Orientation from Gyros

The angular velocity is filtered and then integrated to get the change in angles, relative to the local axis. The evolution of $\theta(t)$ for δt is approximated by Taylor series expansion [8] and for first order integration the error rate is $\frac{1}{2}\omega^2\delta t$, about 0.54^0/sec (for $100Hz$ sampling rate and typical $60^0/sec$ angular velocity). This approximation is valid because performance is limited by the cumulative errors because of the integration of the time-varying bias in the angular velocities. We focus on correcting this error by an accurate estimate of bias during in-use calibration of gyros and correction by accelerometer and magnetometer data.

4.3 Orientation Correction Using Accelerometers and Magnetometers

In semi-static state, there is no significant kinematic linear acceleration, and the signal from the accelerometers can be used as inclinometers giving the gravity vector in local coordinates. Orientation error due to drift in parameters of gyros, is corrected by determining the absolute orientation from the gravity vector and earth's magnetic field $\boldsymbol{H}$ as the reference. The magnetometers give $\boldsymbol{H}$ which maintains a fixed value and direction in absence of magnetic disturbance;this can be detected [7]. Let $\hat{\mathbf{g}} = \frac{\boldsymbol{g}}{|\boldsymbol{g}|}$ be the unit vector of gravity, and $\hat{\mathbf{H}} = \frac{\boldsymbol{H}}{|\boldsymbol{H}|}$ be the unit vector of the earth's magnetic field. Let $\hat{\mathbf{v}} = \boldsymbol{g} * \boldsymbol{H}$ be the unit vector perpendicular to both of them. Let $(\sigma_0, \mu_0, \tau_0)$ represent reference coordinate frame (initial starting position) and $(\sigma_1, \mu_1, \tau_1)$ represent the coordinate frame of rotated local body frame. Then, in reference frame, the unit vectors $\hat{\mathbf{g}}$, $\hat{\mathbf{H}}$ and $\hat{\mathbf{v}}$ can be expressed as:

$$\hat{\boldsymbol{g}} = a_{11}\sigma_0 + a_{12}\mu_0 + a_{13}\tau_0 \tag{8}$$

$$\hat{\boldsymbol{H}} = a_{21}\sigma_0 + a_{22}\mu_0 + a_{23}\tau_0 \tag{9}$$

$$\hat{\boldsymbol{v}} = a_{31}\sigma_0 + a_{32}\mu_0 + a_{33}\tau_0 \tag{10}$$

where a_{1j} and a_{2j} are the estimated values of acceleration and earth's magnetic field and a_{3j} are calculated coefficients in local frame $(\sigma_0, \mu_0, \tau_0)$. Let A represent the matrix formed by a_{ij}. Similarly, in the rotated frame $(\sigma_1, \mu_1, \tau_1)$, the matrix B can be calculated. It contains the coefficients of $\hat{\mathbf{g}}$, $\hat{\mathbf{H}}$ and $\hat{\mathbf{v}}$ in rotated local frame $(\sigma_1, \mu_1, \tau_1)$. We obtain

$$A[\sigma_0\mu_0\tau_0] = B[\sigma_1\mu_1\tau_1] \tag{11}$$

Thus, the transformation matrix $T = B^{-1}A$ gives the absolute orientation which takes us to the current rotated frame from the reference world frame, which is used to obtain driftless orientation by correcting the orientation in the semi-static states.

5 Experiments

5.1 Hardware Description

We test our algorithm on a sensor system prototype fabricated by QCAT (Queensland Centre for Advanced Technologies, CSIRO, ICT Centre) named EiMU. It is comprised of two ADXL202JQC (two-axis) accelerometers (±2g range), three Honeywell's HMC1001/1002 (single axis magnetic sensors with ±2G range), three Analog Device ADXRS150 gyros (single-axis with $\pm150^0/s$ range), containing a D60 HC12 processor board which sends sampled data at 100Hz to the computer.

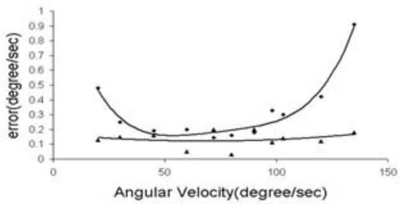
5.2 Results and Discussion

When the device is held still, the error is less than 0.5^0/hour. This is achieved because of the robust static-state detector.

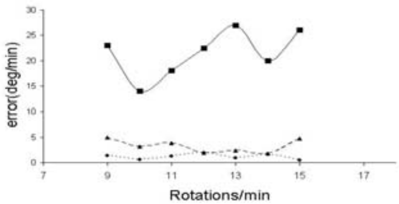
To study dynamic accuracy, experiments were conducted by rotating the device with different angular velocities on a turntable. The Fig. 3(a) shows short-term error in estimating orientation, calculated by gyros only, which optimizes error for frequencies of interest (*i.e.*, which are present in human motion) but gives us mean error of $0.32^0/sec$. Correcting the orientation by accelerometers and magnetometers in semi-static states reduces the error to $0.18^0/sec$.

Fig. 3(b) shows the effect of bias re-estimator. We have large drifts in orientation using gyros alone, which is improved by correction using accelerometers and magnetometers. Using the bias re-estimator reduces dynamic error to less than 2^0 assuming one semi static state per minute.

This is a significant improvement over other orientation trackers using the same sensors. For comparison Xsense [9] achieved 1^0 static accuracy, and 3^0 rms accuracy. Foxlin [1] used external acoustic sensors along with inertial sensors to achieve accuracy of 1.5^0.



(a) Orientation Error for Gyros



(b) Long Term Error Comparison

Fig. 3. (a) Short term orientation error vs. angular velocity in the absense of (upper curve) and in presence of (lower curve) correction by accelerometer and magnetometers (best fit curves of order 3). (b) Long term error in different cases;(1) dark line shows error only caused by gyro, (2) dashed line shows error when only correction by acclerometers and magnetometers is active, (3) dotted line shows error when both bias re-estimation and correction by accelerometers and magnetometers are active. It shows an improvement in performance using our algorithm

6 Conclusion

This paper presents an algorithm to robustly detect multi-level quasi-static states from inertial sensors, allowing the proper re-estimation of the time-varying sensor parameters while the device is in use. The performance of the proposed algorithm was demonstrated by developing a mixed-reality real-time orientation tracker. Thus, we demonstrated that properly estimating the parameters of inertial sensors can help in improving performance. The proposed algorithm is a step towards development of a self-organizing sensory motor system. In the future the system can be improved by applying evolutionary algorithms to finetune the internal parameters and architecture of the motion estimation system.

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