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Improvements in deterministic error modeling and calibration of inertial sensors and magnetometers

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ABSTRACT

and calibration.

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1. Introduction

Inertial sensors were mainly only used in aeronautics and maritime applications until the nineties because of the high cost associated with the high-accuracy requirements. With developments in micro-electro-mechanical systems (MEMS), the availability of small, lower-cost, medium-performance inertial sensors has opened up new possibilities for their use, such as the recognition of daily activities [1], physical therapy and home-based rehabilitation [2], biomechanics [3], detecting and classifying falls [4,5], shock and vibration analysis, navigation of unmanned vehicles [6–8], and state estimation and dynamic modeling of legged robots [9].

Inertial measurement units (IMUs) typically contain gyroscopes and accelerometers, sometimes used in conjunction with magnetometers. Each device can be sensitive around a single axis or multiple axes (usually two or three). An accelerometer detects specific force, which is proportionate to the acceleration of the sensor

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http://dx.doi.org/10.1016/j.sna.2016.06.024 0924-4247/© 2016 Elsevier B.V. All rights reserved. relative to an inertial reference frame along its axis of sensitivity. A gyroscope senses the angular rate about an axis of sensitivity with respect to an inertial reference frame [10,11]. Magnetometers measure the magnetic field strength at a given location superposed with the Earth's magnetic field [12]. They are used in a wide range of disciplines, from archaeology [13] to vehicle navigation and control [14].

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We consider the deterministic modeling, calibration, and model parameter estimation of two commonly

employed inertial measurement units based on real test data acquired from a flight motion simulator.

Each unit comprises three tri-axial devices: an accelerometer, a gyroscope, and a magnetometer. We

perform the deterministic error modeling and calibration of accelerometers based on an improved mea-

surement model, and the technique we propose for gyroscopes lowers costs by eliminating the need for additional sensors and relaxing the test bed requirement. We present an extended measurement

model for magnetometers that reduces calibration errors by modeling orientation-dependent hard-iron

errors in a gimbaled angular position-control machine. While we employ the model-based Levenberg-

Marquardt optimization algorithm for the parameter estimation of accelerometers and magnetometers,

we use a model-free evolutionary optimization algorithm (particle swarm optimization) for estimating

the calibration parameters of gyroscopes. Errors are considerably reduced as a result of proper modeling

Consumer-grade inertial sensors have attracted much interest recently because of their decreasing cost due to developments in MEMS technology [15]. Measurements by inertial sensors often deviate from the ground truth since the devices suffer from various error types, which can be constant or time varying. The rate output of accelerometers and gyroscopes needs to be integrated twice or once to obtain the linear or angular position, respectively. Because of the integration process, even very small errors at the output accumulate very rapidly and the position error becomes considerably large in a few seconds and starts drifting in time (i.e., proportionate with the time cube for the linear and the time square for the angular position) [16]. This effect is exacerbated for low-grade sensors. Consumer-grade inertial sensors can be used for longer periods of time on their own if modeled and calibrated properly, but may need to be corrected from time to time by an external aid that provides an absolute reference for the ground truth [17,18]. Thus, to improve



Fig. 1. The two sensor units used in this study: (a) MicroStrain 3DM-GX2 [22] and (b) Xsens MTx [23].

the accuracy of linear and angular position estimates, it is necessary to characterize and model the errors at the sensor output precisely. The same holds for magnetometers that suffer from various error types.

Most previous works have divided the calibration problem into two distinct parts (*deterministic* and *stochastic* modeling) because of their different mathematical natures [10,19,20]. Here, we follow the same approach and focus on deterministic calibration only. Stochastic calibration is considered in a different study [21].

Working from their raw outputs, we consider the deterministic calibration of two widely used consumer-grade IMUs and compare their performances: MicroStrain's 3DM-GX2 [22] and Xsens' MTx [23], depicted in Fig. 1, with their technical specifications provided in the respective references. The units are small, light, and comprised of three tri-axial devices: an accelerometer, a gyroscope, and a magnetometer. The main objective of this study is to effectively model and estimate the units' deterministic calibration parameters so that both their stand-alone and aided performances can be improved.

Motivated by insights gained from earlier work, we propose improved models and algorithmic ideas and implement them to improve the sensor calibration process. The main contributions of this article are threefold:

- We propose an improvement to the traditional measurement model used in 1g tests for modeling the deterministic errors of accelerometers. The method's effectiveness is shown through experiments, and the results are compared with those of the traditional model.
- We employ a low-cost calibration technique to estimate the error components associated with gyroscopes. Our technique is based on comparing the attitude of the IMU, calculated by integrating the gyroscope measurements, with the reference attitude provided by a 3-DoF flight motion simulator (FMS). In this way, we eliminate the need for any additional sensors to perform the calibration, unlike previously used low-cost gyroscope calibration techniques. Another novel aspect of this work is that to estimate the model parameters that minimize the attitude error of gyroscopes, we use a global optimization algorithm [particle swarm optimization (PSO)] instead of gradient-based techniques, to avoid convergence to local minima.
- We propose an extended sensor measurement model for magnetometers that reduces calibration errors by modeling the orientation-dependent magnetic disturbances in gimbaled angular position-control machines. We experimentally verify that incorporating in the model the relative motion between the magnetometer and the magnetic distortion sources in the environment enhances the calibration accuracy.

The rest of this article is organized as follows: In Section 2, we first develop individual deterministic sensor measurement models for each type of sensor and then propose a unified measurement model for all three sensor types. Section 3 describes the data acquisition experiments conducted for calibrating the sensors and briefly reviews geometric and algebraic parameter estimation techniques. We then present our model parameter estimation results based on the acquired data and propose an extended measurement model for magnetometers. We compare the two units in terms of measurement quality based on the results of deterministic calibration. In Section 4, we summarize our contributions, make concluding remarks, and provide some directions for future research. In the appendices, we provide background information on the two optimization algorithms that we use for parameter estimation.

2. Sensor measurement models

The general measurement model of the sensors evaluated in this study is given by:

$$\vec{e}_m = h(\vec{e},\theta) + \vec{n} \tag{1}$$

where $\vec{h}(\vec{e}, \vec{\theta}) : \mathbb{R}^3 \times \mathbb{R}^{\dim(\vec{\theta})} \to \mathbb{R}^3$. The \vec{e}_m , \vec{e} , and $\vec{n} \in \mathbb{R}^3$ denote the measured sensor output, the true value of the excitation signal, and the additive stochastic measurement noise vector, respectively. The calibration parameter vector $\vec{\theta}$ involved in this model needs to be estimated accurately in the scope of deterministic calibration.

The following notation is used throughout: The measured sensor output \vec{e}_m can be one of \vec{a}_m , $\vec{\omega}_m$, or \vec{B}_m , for the accelerometer, gyroscope, and magnetometer, respectively. The true excitation signal \vec{e} can be one of \vec{a} , $\vec{\omega}$, or \vec{B} , which represent the true values of the specific acceleration, angular rate, and magnetic field strength vectors. A vector \vec{u} expressed with respect to a coordinate frame f is denoted by \vec{u}^f , and the rotational transformation matrix $\mathbf{C}_{f_1}^{f_2}$, transforms a vector \vec{u}^{f_1} from frame f_1 to f_2 as $\vec{u}^{f_2} = \mathbf{C}_{f_1}^{f_2} \vec{u}^{f_1}$. Orthonormal unit vectors of the x, y, and z axes of a given frame f are respectively denoted by \vec{i}^f , \vec{j}^f , and \vec{k}^f .

To develop the deterministic measurement model of the sensors, we first need to introduce several coordinate frames:

- **the north-east-down (NED) frame** is shown in Fig. 2, with unit vectors \vec{i}^{NED} , \vec{j}^{NED} , and \vec{k}^{NED} , which point to the north, east, and down directions of the Earth, respectively.
- **the platform base frame** (*p*) is an orthogonal frame fixed to the base of the rotating platform onto which the sensor units are mounted, and does not move with the platform.
- **the sensor enclosure frame** (*q*) corresponds to the orthogonal axes of the sensor's mechanical casing. Due to manufacturing tolerances and packaging issues, in practice, this frame cannot

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