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Comparison of calibration methods for accelerometers used in human motion analysis

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ABSTRACT

In the fields of medicine and biomechanics, MEMS accelerometers are increasingly used to perform activity recognition by directly measuring acceleration; to calculate speed and position by numerical integration of the signal; or to estimate the orientation of body parts in combination with gyroscopes. For some of these applications, a highly accurate estimation of the acceleration is required. Many authors suggest improving result accuracy by updating sensor calibration parameters. Yet navigating the vast array of published calibration methods can be confusing. In this context, this paper reviews and evaluates the main measurement models and calibration methods. It also gives useful recommendations for better selection of a calibration process with regard to a specific application, which boils down to a compromise between accuracy, required installation, algorithm complexity, and time.

1. Introduction

Because microelectromechanical system (MEMS) development has resulted in sensors being cheap and small, accelerometers have been used in many applications. Recently, they have even invaded our daily lives with the influx of smartphones and connected objects. In practice, accelerometers are used for two main purposes: to directly obtain and interpret acceleration measure, to estimate another measure (such as orientation or position by integrating the acceleration), or by fusion with other measures (typically angular velocity).

Acceleration is used directly for vibration measurement on a mechanical structure. For example, the analysis of vibration on rotating machinery can give information to diagnose defects and initiate maintenance operations. Another way to interpret vibration is modal analysis, which is the analysis of the dynamic response of a structure under vibrational excitation. For example, this enables us to check that a building's natural frequency does not match that of earthquakes.

The acceleration measure can also be directly interpreted in the fields of medicine and biomechanics especially for activity recognition [1]. The identification of known patterns over accelerations measured from body segments can identify a range of static and dynamic activities [2]. Typical applications are analysis of activities of daily living to improve rehabilitation treatment [3] and fall detection for the elderly [4]. Other less expected applications include the analysis of accelerometric patterns from gait for biometric user identification [5].

Regarding indirect measures based on acceleration, accelerometers are often used in static condition to estimate orientation. Indeed, 3D measured acceleration can be compared with g (vertical gravitational acceleration) and can provide two orientation angles, which are often described as roll and pitch angles. However, to estimate the full orientation parameters, that is to estimate the rotation along the vertical axis as well, accelerometers are not sufficient and are associated with magnetometers that provide an estimation of yaw angle [6,7]. In this way, Kemp et al. [8] measured 3D orientation of body parts for diagnosis of movement disorders. In non-static conditions however, accelerometers measure the combination of gravity and external acceleration, which means that orientation cannot be estimated properly [9]. Luinge et al. [10] succeeded in estimating body inclination during movements with large accelerations from a 3D accelerometer using Kalman filtering and making assumptions concerning the frequency of the movement measured. In fact, for 3D orientation measures, accelerometers are most often combined with gyroscopes to form an inertial measurement unit (IMU). Regarding these IMUs, algorithms were developed on the initiative of NASA, to integrate inertial data for spatial navigation [11]. Inertial navigation systems (INS) are now widely used in the spatial, aeronautic and military fields for spacecraft, plane and missile guidance. In the field of biomechanics IMUs are used to perform movement analysis and

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postural evaluation. For example, El-Gohary et al. [12] use IMUs to detect and characterize turns during gait in patients with Parkinson's disease. Al-Jawad et al. [13] use Kalman filtering, which is an excellent tool for data fusion coming from noisy signals, for static postural sway analysis from IMU data. The association of IMU and Kalman filtering enabled El-Gohary and McNames [14] to measure human joint angles, Sabatini [15] to perform gait analysis, and Zhang et al. [16] to apply pose estimation for cycling.

Apart from orientation, IMU accelerometers can also estimate speed and position [17]. Indeed, using attitude estimated by the fusion of accelerometer and gyroscope data, acceleration can be expressed in the global frame. Then, by computing a double integration, the velocity and the position of the sensor from the starting point can be estimated. Following this method, IMU has become a promising device for human localization, and particularly for indoor pedestrian tracking [18]. Indeed it can be an alternative to global navigation satellite systems because the satellite signals are often too weak to penetrate buildings.

For all of these applications, the relevance of results directly depends on the accuracy of the collected data. For example, in the particular case of position estimation, the accuracy of measured acceleration is a crucial point. Indeed, orientation is first estimated from the fusion of gyroscope and accelerometer data, after which acceleration can be expressed in the global frame. However, the second step is to double integrate acceleration to track changes in the IMU's position. Due to the propagation of measurement errors through projection and integration calculations, errors rapidly accumulate in the tracked position. Such errors are collectively referred to as drift.

In the literature, two categories of measurement errors are distinguished: stochastic errors (noise) and deterministic errors (calibration defects). Firstly, electronic sensors are disturbed by noise [19]. Thermal noise has the main influence on data collected from electronic sensors. As it is usually modeled with a Gaussian white noise, it has an impact over the entire frequency domain such that it cannot be filtered. Secondly, the definition of the link between raw output signals and estimated acceleration can be a factor of loss of accuracy. Unlike noise, this error can be corrected by defining an adapted measurement model and following an accurate calibration process. From the literature, measurement models with different levels of complexity can be selected, and several calibration methods have been described for accelerometers [20–24].

IMUs are commonly grouped into four performance categories: marine/navigation, tactical, industrial, and automotive/consumer grade. Marine/navigation grade sensors are the most precise, based on mechanical technology. Due to their high cost (from 100 000 to 1 million dollars) they are typically used in submarines, spacecraft, and military aircraft. Industrial and automotive categories are composed of sensors based on MEMS technology, and their main difference lies in the quality of sensor calibration.

This paper focuses on calibration methods for MEMS accelerometers which are intended to be used in human motion analysis. As papers dealing with sensor calibration are flooding scientific literature, choosing an adapted approach for accelerometer calibration can be confusing. For clarification, the two following sections review the classical models and calibration procedures that are most commonly described in the literature. As one of the most important comparison criteria for these methods is their accuracy, the fourth section of this paper evaluates the magnitude of the errors resulting from each selected calibration method. Finally, the fifth section of this paper discusses these results and compares calibration methods, taking into account other criteria such as calculation complexity, consumed time, and required equipment. This paper concludes by offering some recommendations for the selection of a calibration method.

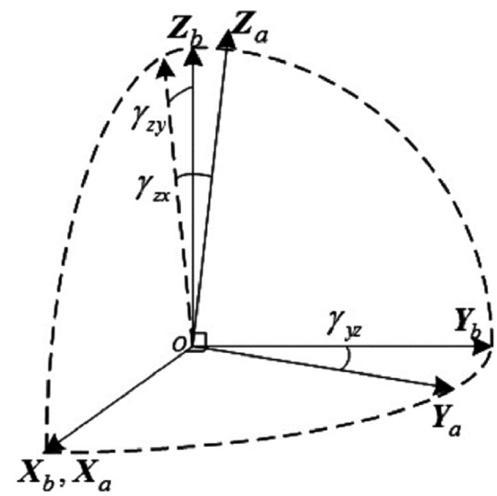

Fig. 1. Definition of the orthogonal frame built from the three accelerometer axes by three small rotations γ_{yx}, γ_{zx} and γ_{zy} (from Cai et al. [22]).

2. Measurement models

Ideally, an accelerometer would have exactly the same sensitivity at any amplitude point within its specified amplitude range. It is generally agreed that the measurement model can be considered as linear when environmental conditions (temperature, for example) are sufficiently steady. The limit to how far the accelerometer's output will differ from this perfect linearity is specified by the manufacturer in the datasheet. The measurement model for a perfectly linear accelerometer can be written as follows:

$$a = s.(u - b) \tag{1}$$

where a is the acceleration estimated from the electric potential u given by the sensor, by means of a scale factor s and an offset b.

2.1. First model

For 3D acceleration measurements, the first model can be written in a matrix form:

$$\boldsymbol{a} = \boldsymbol{S} \ . \ (\boldsymbol{u} - \boldsymbol{b}) \tag{2}$$

with

$$\boldsymbol{a} = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}; \quad \boldsymbol{S} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & s_z \end{bmatrix}; \quad \boldsymbol{u} = \begin{bmatrix} u_x \\ u_y \\ u_z \end{bmatrix}; \quad \boldsymbol{b} = \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} \tag{3}$$

The link between sensor outputs and acceleration is defined via six calibration parameters (three scale factors and three offsets). This model is based on the restrictive assumption that the three axes of the accelerometers are perfectly orthogonal. Because of this limitation, this model is rarely used [20].

2.2. Second model

Due to the imprecise nature of the construction of a triaxial accelerometer, the three axes cannot be perfectly orthogonal. By defining three small rotations, starting from the first axis of accelerometers, an orthogonal frame can be defined (Fig. 1). Many authors define the link between real axes of accelerometers and the new orthogonal frame by a matrix $\boldsymbol{T}$ [21,22,25,26], such that the model becomes:

$$\boldsymbol{a} = \boldsymbol{T} \ . \ \boldsymbol{S} \ . \ (\boldsymbol{u} - \boldsymbol{b}) \tag{4}$$