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A Review of Wearable IMU (Inertial-Measurement-Unit)-based Pose Estimation and Drift Reduction Technologies

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A Review of Wearable IMU (Inertial-Measurement-Unit)-based Pose Estimation and Drift Reduction Technologies

Jingdong ZHAO

Academic of Electrical and Informational Engineering, Hunan University, Changsha, Hunan, China

390742348@qq.com

Abstract. Accurate tracking of the orientation of a rigid object is important in several domains, such as sports training, rehabilitation and animation. As technology develops, IMU-based method becomes an increasingly popular approach for navigation and motion tracking. However, IMUs suffer from integration drift. As a result, technologies for reduction of the integration drift are important and meaningful. In this paper, we gave a review on principles of IMU-based pose estimation methods, introduced an integration drift reduction method called Kalman Filter and discussed the proper application fields for wearable IMU. Compared to other sensor used for pose estimation, wearable IMU has better self-independence, leading to its validity in all the environments, and it can provide good real-time estimation at a small cost of money and power.

1. Introduction (Heading 1)

Accurate tracking of the orientation of a rigid object is important in several domains, such as sports training, rehabilitation and animation [1-4]. Several technologies and approaches are available to produce motion tracking systems (trackers). However, most current sensing approaches for motion tracking need the availability of external sources, e.g., cameras for optical trackers, ultrasonic/electromagnetic transmitters for acoustic/electromagnetic trackers. Usually, the sources can operate only over relatively short distances, which makes the trackers highly susceptible to interference and line-of-sight occlusion (shadowing): hence, proper functioning of these trackers is only possible within carefully controlled experimental setups (motion analysis laboratories). This fact precludes, for instance, the quantitative assessment of the behavior of a human subject in unrestrained.

As technology develops, one increasingly popular approach for navigation and motion tracking is based on inertial sensors, which is also called an inertial measurement unit (IMU). An IMU is usually composed of an accelerometer and a gyroscope. Sometimes, it can be combined with a magnetometer to work as an inertial navigation system. Today, wearable IMUs have been widely used in various domains, including biomedical engineering [5], virtual reality [6] and real-time tracking of human action in the three-dimensional (3D) space [7]. Although they are a promising choice as wearable sensors under many respects, the inertial and magnetic sensors currently in use offer measuring performance that are critical in order to achieve and maintain accurate 3D-orientation estimates, anytime and anywhere.

IMUs are a promising choice as wearable sensors for motion tracking under many respects. One of the advantages is that IMUs are totally sourceless. Since an accelerometer and a gyroscope measures the linear accelerations and angular velocities respectively, which are related to the motion of the objects where the sensors are fixed, an IMU is a completely self-contained approach. Although sometimes it is combined with a magnetometer, which is externally referenced, the ubiquitous presence of a magnetic field on earth makes the magnetic source available almost everywhere.

However, IMUs suffer from integration drift. Small errors appear during the measurement of acceleration and angular velocity, and they will progressively be integrated into larger errors in velocity and angle, which are compounded into still greater errors in position [8]. As the current position is updated from the previous calculated one and the measured acceleration and angular velocity, these errors accumulate roughly proportionally to the time. As a result, technologies for reduction of the integration drift are important and meaningful. In this paper, we give a review on how an IMU is used for pose estimation and how researchers achieve integration drift reduction.

The rest of the paper is as follows: Section II is divided into three parts, where we respectively introduce the pose representation methods, the principle of IMU-based pose estimation and the most popular IMU data fusion technology; in Section III, we discuss the proper applications for IMU-based pose estimation. Finally, we make a conclusion in Section IV.

2. Methods

2.1. Representation of Pose

To solve the problem of pose estimation, it is necessary to have proper methods to represent the orientation of a rigid body with a fixed coordinate system. There're several ways of mathematicians for pose representation, among which Euler angles, Tait-Bryan angles and quaternions are the most famous ones.

Two coordinate systems are used to describe the orientation: the earth-fixed coordinate system and a non-inertial coordinate system. The earth-fixed coordinate system is also called an inertial one, specified by the right-handed orthonormal basis $E = \{\boldsymbol{e}_1 \quad \boldsymbol{e}_2 \quad \boldsymbol{e}_3\}$ whose x-, y- and z-axis are directed in the local north, east and down directions (NED). The non-inertial coordinate system, also named as body-fixed coordinate system, is specified by the right-handed orthonormal basis $B = \{\boldsymbol{e}_1' \quad \boldsymbol{e}_2' \quad \boldsymbol{e}_3'\}$ whose X-, Y- and Z-axis are conventionally called "out the nose", "out the right side" and "out the belly" in the aeronautics jargon, as shown in Fig. 1.

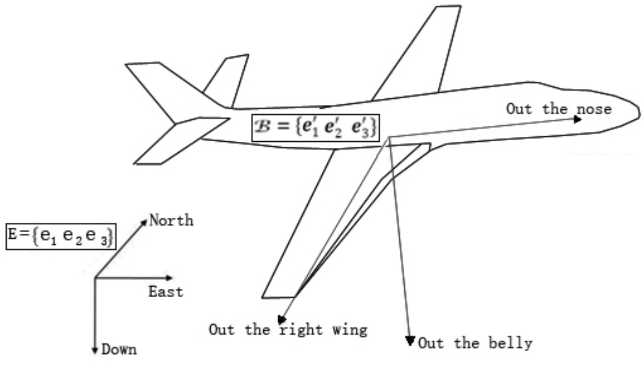

Fig. 1. Earth-fixed frame and body-fixed frame on a toy aircraf.

A general rotation in three dimensions can be divided into several basic rotations. A basic rotation (also called elemental rotation) of the non-inertial coordinate system is defined as a rotation about one of the axes of a coordinate system. In Euclidean space, three basic rotation matrices (1-3) are used to represent the rotation by an angle θ about the x-, y-, and z-axis respectively.

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix} \tag{1}$$

$$R_y(\theta) = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} \tag{2}$$

$$R_z(\theta)=\begin{bmatrix}\cos\theta & -\sin\theta & 0\\ \sin\theta & \cos\theta & 0\\ 0 & 0 & 1\end{bmatrix} \qquad (3)$$

By using matrix multiplication, the matrix representing a general rotation can be obtained from (1-3). For example, the product in (4)

$$R=R_z(\alpha)R_y(\beta)R_x(\gamma) \qquad (4)$$

represents a rotation of first γ about x-axis, of β about y-axis and finally of α about z-axis. And the rotation is called extrinsic rotations, occurring about the axes of the fixed coordinate system xyz. Meanwhile, (4) can also be regarded as a rotation of first α about Z-axis, β about Y-axis and γ about X-axis, if we start with XYZ axes overlapping xyz axes. This representation is defined as intrinsic rotations which occur about the axes of the XYZ attached to the non-static rigid body.

In 1776 the Euler angles are introduced to describe the pose of a rigid body by Leonhard Euler with respect to a fixed coordinate system [9]. Euler angles which are angles typically denoted as φ, θ andψ are Defined by extrinsic rotations, the Euler angles can represent a general rotation as (5):

$$R=R_z(\psi)R_x(\theta)R_z(\varphi). \qquad (5)$$

The Euler angles used to be called as proper or classic Euler angles in the 19th century. A second type of formalism called Tait–Bryan angles [10] are brought up by Peter Guthrie Tait and George H. Bryan. Denoted as α, β andγ, Tait-Bryan angles typically represent an intrinsic rotation of α, β,γ about axes Z, Y, Xin sequence respectively, as (6):

$$R=R_Z(\alpha)R_Y(\beta)R_X(\gamma). \qquad (6)$$

Tait–Bryan angles are helpful for aerospace applications. For an aircraft, a pose change can be obtained with three rotations around its principal axes and in the proper order. The bearing, a pitch will yield the elevation and a roll gives the bank angle will be obtained by a yaw. Therefore, in aerospace yaw, pitch and roll sometimes represent Tait–Bryan angles.

The quaternion representation is an advanced method compared to Euler angles, because with a single rotation it has a rotation matrix about one axis and has no singularity problem [11]. A quaternion with one real number and three imaginary numbers is shown in (7):

$$q=q_0+q_v=q_0+(q_1\boldsymbol{i}+q_2\boldsymbol{j}+q_3\boldsymbol{k}). \qquad (7)$$

and q_0, q_1,q_2 and q_3 are real numbers. We can achieve rotating of a 3D vector from v to v' as shown in (8) with $q$and its conjugate, denoted as q^*.

$$v'=q\cdot v\cdot q^* \qquad (8)$$

When a unit quaternion is used, (9) and (10) is as followed.

$${q_0}^2+({q_1}^2+{q_2}^2+{q_3}^2)=1 \qquad (9)$$

$$q=q_0+q_v=\cos(\theta)+u\sin(\theta) \qquad (10)$$

u is a 3D unit vector($u=u_xi+u_yj+u_zk$). In this case, the vector v' is the rotation of v by an angle θ about the vector u. We know the quaternion components of $q$are as (11), Combine (9) and (10),.

$$\begin{cases} q_0=\cos\frac{\theta}{2}\\ q_1=u_x\sin\frac{\theta}{2}\\ q_2=u_y\sin\frac{\theta}{2}\\ q_3=u_2\sin\frac{\theta}{2}\end{cases} \qquad (11)$$

The differential equation of quaternion q with respect to time has the following matrix form:

$$\dot{q_k}=\frac{1}{2}Q_k\cdot\omega_k \qquad (12)$$

$$\begin{bmatrix}\dot{q_0}\\ \dot{q_1}\\ \dot{q_2}\\ \dot{q_3}\end{bmatrix}=\frac{1}{2}\begin{bmatrix}q_0 & -q_1 & -q_2 & -q_3\\ q_1 & q_0 & -q_3 & q_2\\ q_2 & q_3 & q_0 & -q_1\\ q_3 & -q_2 & q_1 & q_0\end{bmatrix}\cdot\begin{bmatrix}0\\ \omega_x\\ \omega_y\\ \omega_z\end{bmatrix} \qquad (13)$$

Then, the quaternion terms after rotation are

$$q_k=\dot{q_{k-1}}\cdot\Delta t+q_{k-1} \qquad (14)$$

where q_k is the quaternion at the kth term, and Δt is the sampling time. In this way, we can represent a rotation by quaternions or its differential form.

2.2. Principle of IMU-based Pose Estimation

Since Euler angles are easier for explaining the principle, we take Euler angles into consideration in this part. Here we discuss the $Z-Y-X$intrinsic rotation sequence, which are the Tait-Bryan angles. Start with XYZ axes of the body-fixed frame overlapping xyz axes of the reference orientation. First, the body is rotated about Z-axis through yaw an angle denoted as γ, or heading angle($\gamma \in [-\pi,\pi]$); second, the object is rotated about the Y-axis through pitch or elevation an angle denoted as β ($\beta \in \left[-\frac{\pi}{2},\frac{\pi}{2}\right]$); third, the object is rotated about the nose axis through a roll angle or bank angle α, so as to match the body-fixed frame ($\alpha \in [-\pi,\pi]$). We can then write:

$$x_B=\begin{bmatrix}1 & 0 & 0\\ 0 & c_\varphi & s_\varphi\\ 0 & -s_\varphi & c_\varphi\end{bmatrix}\begin{bmatrix}c_\vartheta & 0 & s_\varphi\\ 0 & c_\varphi & 0\\ s_\vartheta & 0 & c_\vartheta\end{bmatrix}\begin{bmatrix}c_\psi & s_\psi & 0\\ -s_\psi & c_\psi & 0\\ 0 & 0 & 1\end{bmatrix}x_E \tag{15}$$

$$R(\psi,\vartheta,\varphi)=\begin{bmatrix}c_\vartheta c_\psi & c_\vartheta c_\psi & -s_\vartheta\\ s_\varphi s_\vartheta c_\psi - c_\vartheta c_\vartheta & s_\varphi s_\vartheta c_\psi + c_\vartheta c_\vartheta & c_\vartheta s_\varphi\\ c_\varphi c_\psi s_\vartheta + s_\psi s_\varphi & c_\varphi c_\psi s_\vartheta - s_\psi s_\varphi & c_\vartheta c_\varphi\end{bmatrix} \tag{16}$$

For an accelerometer, it measures the gravity in three axes of the body-fixed coordinate system, which represent gravity vector in the body-fixed coordinate system as follows:

$$g_B=\begin{bmatrix}c_\vartheta c_\psi & c_\vartheta c_\psi & -s_\vartheta\\ s_\varphi s_\vartheta c_\psi - c_\vartheta c_\vartheta & s_\varphi s_\vartheta c_\psi + c_\vartheta c_\vartheta & c_\vartheta s_\varphi\\ c_\varphi c_\psi s_\vartheta + s_\psi s_\varphi & c_\varphi c_\psi s_\vartheta - s_\psi s_\varphi & c_\vartheta c_\varphi\end{bmatrix}\begin{bmatrix}g\\ 0\\ 0\end{bmatrix}=g\begin{bmatrix}-s_\vartheta\\ s_\varphi c_\vartheta\\ c_\varphi c_\vartheta\end{bmatrix} \tag{17}$$

This is the principle of the accelerometer-based pose estimation, which shows that heading information isn't conveyed through a body-fixed tri-axial accelerometer.

We use the following system of first-order nonlinear differential equations [11], since a gyroscope measures the angular velocity about the three axes of the body-fixed frame$\boldsymbol{\omega}_B=[p \quad q \quad r]^T$:

$$\begin{bmatrix}\frac{d\varphi}{dt}\\ \frac{d\theta}{dt}\\ \frac{d\psi}{dt}\end{bmatrix}=\begin{bmatrix}1 & \frac{s_\varphi s_\vartheta}{c_\vartheta} & \frac{s_\varphi s_\vartheta}{c_\vartheta}\\ 0 & c_\varphi & -s_\varphi\\ 0 & \frac{s_\varphi}{c_\vartheta} & \frac{c_\varphi}{c_\vartheta}\end{bmatrix}\begin{bmatrix}p\\ q\\ r\end{bmatrix} \tag{18}$$

This is the principle of the gyroscope-based pose estimation method that can be used to update the orientation of the rigid body in time given the angular velocity. Concerning all unconstrained representations of orientation, Euler angles suffer from singularities, commonly referred to as gimbal-lock: for instance, in the case of the $Z-Y-X$ rotation sequence, if thepitch angle β is ± π/2, the last two terms of the first and last rows in (18) go to infinite and the Euler angle integration becomes indeterminate. In this case, the pose representation using quaternions shows its advantage.

2.3. Fusion of IMU Data

Although both accelerometer and gyroscope can work for orientation estimation alone, either of them have its own limitation in application [12]. Only when the IMU keeps still or moves in a very slow motion, the accelerometer is effective. High motion speed will bring high frequency noise to its acceleration measurement. On the other hand, the gyroscope works well only when the IMU rotates fast, for the drifts in still situation will be integrated through time and cause big errors. To solve the problem, like Kalman Filter, the most common data fusion algorithms, should be applied. The block diagram of orientation estimation principles for an IMU is shown in Fig. 2.

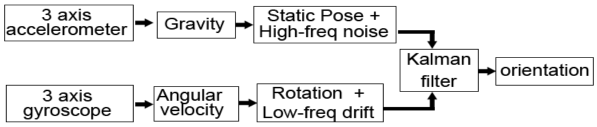

Fig. 2. Block diagram of orientation estimation principles for an IMU.

There are several ways to fuse the IMU data. Extended Kalman Filter (EKF) is the most popular and famous algorithm . EKF use a state vector and a measurement vector which composed of rotation quaternion $\vec{q}_{k+1}$ of the femoral head and gyro bias vector ${}^{g}\vec{b}_{k+1}$. ${}^{q}\vec{w}_{k}$and${}^{m}\vec{w}_{k}$are noise vectors of accelerometer and magnetometer respectively. The state vector $\vec{x}_{k+1}$could be expressed as

$$\vec{x}_{k+1} = \begin{bmatrix} \vec{q}_{k+1} \\ {}^{g}\vec{b}_{k+1} \end{bmatrix} = f(\vec{x}_k, \vec{u}_k) + \vec{w}_k \qquad (19)$$

The nonlinearity is introduced by the exponential term in the matrix. By stacking the accelerometer $\vec{a}_{k+1}$and magnetometer measurement vectors$\vec{m}_{k+1}$, as shown in (20), the measurement vector $\vec{z}_{k+1}$of the proposed Kalman filter is constructed.

$$\vec{z}_{k+1} = \begin{bmatrix} C_b^f(q_{k+1}) & 0 \\ 0 & C_b^f(q_{k+1}) \end{bmatrix} \begin{bmatrix} \vec{g} \\ \vec{h} \end{bmatrix} + \begin{bmatrix} {}^{a}\vec{b}_{k+1} \\ {}^{m}\vec{b}_{k+1} \end{bmatrix} + \begin{bmatrix} {}^{a}\vec{v}_{k+1} \\ {}^{m}\vec{v}_{k+1} \end{bmatrix} (20)$$

where $\vec{g}$and $\vec{h}$ are earth gravity vector and earth magnetism vector respectively in body frame B. $\vec{b}_{k+1}$and$\vec{v}_{k+1}$are the bios vector and noise vector respectively.

EKF estimates the state vector iteratively, whose specific processing steps are listed below.

a) Consider the last filtered state estimate$\hat{\vec{x}}(k)$.

b) Calculate the Jacobian Matrix$F(k)$ for the system dynamics around $\hat{\vec{x}}(k)$.

c) Apply the prediction step of the Kalman filter to the linearized system dynamics obtained in the last step, yielding $\hat{\vec{x}}(k+1)'$ and $P(k+1)'$in (21) and (22).

$$\hat{\vec{x}}(k+1)' = f\left(\hat{\vec{x}}(k), \vec{u}(k)\right) \qquad (21)$$

$$P(k+1)' = F(k)P(k)F^T(k) + Q(k) \qquad (22)$$

$Q(k)$ is the process noise covariance matrix, $P(k)$ is the covariance of $x(k)$ and $P(k+1)'$ is the estimate of the covariance of $x(k+1)$.

d) Linearize the observation dynamics $\vec{z}_{k+1}$ as

$$H(k+1) = \nabla h_k|_{\hat{x}(k+1)'} \qquad (23)$$

e) Apply the filtering cycle of the Kalman filter to the linearized observation dynamics, yielding $\hat{\vec{x}}(k+1)$ and $P(k+1)$ in (24) and (25) respectively.

$$\hat{\vec{x}}(k+1) = \hat{\vec{x}}(k+1)' + K(k+1)\left[\vec{z}_{k+1} - h\left(\hat{\vec{x}}(k+1)'\right)\right] \quad (24)$$

$$P(k+1) = [I - K(k+1)H(k+1)]P(k+1)' \qquad (25)$$

where $R(k)$ is the noise covariance of the measurement model and $K(k)$ is called Kalman gain for iteration k.

3. Applications of IMU-based Method

As we have introduced above, the most distinct function of IMU is pose and position estimation. Classic IMU is composed of a mechanical accelerometer and a mechanical gyroscope, which are quite huge in size and is used on ships or planes for navigation. Nowadays, as MEMS (Micro-electromechanical Systems) technology develops, MEMS IMUs become popular and they are very precise, small and cheap. These advantages lead to a widely use of IMUs in all kinds of wearable systems. The applications of wearable IMU can be basically summarized as the following categories:

3.1. Navigation
Similar to the use of classic IMU, MEMS IMU is also used on different kinds of vehicles as navigators. What's more, almost all the mobile phones produced within five years have MEMS IMU integrated inside, which cooperates with GPS to achieve real-time navigation when you are travelling.

3.2. Pose Control
Keeping balance is one of the most important tasks in controlling a robot, a quadcopter or a self-balancing unicycle. MEMS IMUs are sure to be found on these devices. They are used to estimate the real-time pose of the implanted device, and are combined with negative feedback to keep the device's balance. Such a technology is then migrated on entertainments. There are different phone games being controlled by the pose of your phone.

3.3. Location
People have done many researches on indoor location, among which IMU-based and RFID (Radio Frequency Identification)-based technologies are more popular and is now being fused together. For outdoor cases, RFID becomes invalid and a camera-IMU-based localization will be used instead. One typical case of outdoor localization is automatic driving.

3.4. Gait measurement
Another important application is gait measurement, which is based on different purposes. Kinesiologists use IMU-based gait measurement to analyze the movement of athletes, while normal people use a pedometer or an IMU-included watch for health caring. This technology is also used on fall detection, which is designed in some products specific for old people.

4. Conclusion
In this review, we go through the principles of IMU-based pose estimation. As an accelerometer and a gyroscope are complementary in pose estimation, we also introduce the famous data fusion algorithm, named Kalman Filter. We discuss 4 main proper application categories of MEMS IMU. IMU-based pose estimation method dose have some advantages. It has good self-independence and can work in all environment. It has small data throughput and can provide good real-time estimation. IMU can provide detailed and accurate object's angular and motional information by fusing its data with Kalman filtering algorithm. However, the drifting problem is still significant, and it's meaningful to research on a better method to eliminate the influence of IMU drifts.

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