A Sequential Orientation Kalman Filter for AHRS Limiting Effects of Magnetic Disturbance to Heading Estimation

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Abstract – This paper deals with three dimensional orientation estimation algorithm for an attitude and heading reference system (AHRS) based on nine-axis inertial/magnetic sensor signals. In terms of the orientation estimation based on the use of a Kalman filter (KF), the quaternion is arguably the most popular orientation representation. However, one critical drawback in the quaternion representation is that undesirable magnetic disturbances affect not only yaw estimation but also roll and pitch estimations. In this paper, a sequential direction cosine matrix-based orientation KF for AHRS has been presented. The proposed algorithm uses two linear KFs, consisting of an attitude KF followed by a heading KF. In the latter, the direction of the local magnetic field vector is projected onto the heading axis of the inertial frame by considering the dip angle, which can be determined after the attitude KF. Owing to the sequential KF structure, the effects of even extreme magnetic disturbances are limited to the roll and pitch estimations, without any additional decoupling process. This overcomes an inherent issue in quaternion-based estimation algorithms. Validation test results show that the proposed method outperforms other comparison methods in terms of the yaw estimation accuracy during perturbations and in terms of the recovery speed.

Keywords: Sequential Kalman filter, Attitude and heading reference system (AHRS), Magnetic disturbance, Orientation, Direction cosine matrix (DCM)

1. Introduction

Owing to the rapid progress in the development of miniature inertial sensors such as accelerometers and gyro, the wearable inertial motion capture system has been extensively used for human motion tracking, for example, in entertainment, sports science, and physical medicine and rehabilitation [1-3]. When it comes to the inertial human motion capture, the reliable estimation of three dimensional (3D) orientation is of substantial importance [4]. This paper presents a 3D orientation estimation algorithm for an attitude and heading reference system (AHRS) based on signals collected from a nine-axis inertial/magnetic sensor consisting of a three-axis gyroscope, a three-axis accelerometer, and a three-axis magnetometer.

In the process of orientation estimation using inertial/magnetic sensor signals, the accelerometer and magnetometer measurements provide two “constant” reference vectors to compensate for the drift caused by gyro signal integrations: a) the gravity vector used for the vertical reference, and b) the local magnetic field vector used for the horizontal reference. However, there are two undesirable conditions that cause deterioration of the orientation estimation, as follows. The first condition is kinematically undesirable when the sensor undergoes acceleration. In that case, the accelerometer signal is equal to the sum of the gravity and external accelerations. The other is magnetically undesirable when the sensor is in the vicinity of ferromagnetic objects. Correspondingly, in that case the magnetometer signal is the sum of the local magnetic field and the magnetic disturbance field. From a practical point of view, extended operations under kinematically undesirable conditions are rare in human motions. This is because typical human motions pertain to slow motion conditions, particularly in the case of the elderly and patients [5]. However, the magnetic disturbance issue is more problematic because it is possible for the magnetometer to be exposed to structural magnetic disturbances instead of temporary disturbances [6-8].

In terms of 3D orientation representation, quaternion is arguably considered as the most popular representation owing to its calculation efficiency and singularity-free advantages [4, 5, 9]. Nonetheless, the quaternion has a critical drawback related to the aforementioned magnetic disturbance issue. The magnetometer measurements affect not only yaw estimation but also roll and pitch estimations. Note that only the gyro and accelerometer measurements provide sufficient information to calculate the attitude (i.e., roll and pitch) [10]. Therefore, it is better not to use magnetic data in the calculations of attitude.

In literature, there are some approaches that limit the
effects of magnetic disturbances to the estimation of yaw (or heading) in the quaternion representation so that estimations of roll and pitch are unaffected from the disturbances. Contrary to the conventional quaternion estimator (QUEST) that solves Wahba’s problem [11] in the context of spacecraft attitude determination, Yun et al. [12] proposed the so-called factored quaternion algorithm (FQA) that can decouple the accelerometer and magnetometer signals, and eliminate the effect of magnetometer signals for roll and pitch estimations. Suh [13] proposed an approach that separates the measurement update equation of the corresponding Kalman filter (KF) into two stages: accelerometer measurement update and then magnetometer measurement update. Furthermore, Suh et al. [14] proposed another approach that discards roll and pitch information contained in the magnetometer measurement in the process of quaternion-based indirect orientation KF. These complicated separation processes curtail the merit of quaternion in terms of its calculation efficiency. As an orientation representation, the direction cosine matrix (DCM) is physically intuitive, and is convenient to use in other processes, since it can be used without amendments [15]. However, the DCM is not very popular owing to the number of its components (i.e., nine components).

In fact, a unique DCM can be determined by estimating two unit vectors (i.e., six components) – one vector represents attitude, and the other represents heading. This paper proposes a novel DCM-based orientation estimation algorithm for an AHRS.

This paper is organized as follows. In Section II, the problem addressed in this paper is defined and a sequential orientation KF for AHRS is introduced. In Section III, experimental results are provided to compare the proposed method to the existing methods under various conditions. Discussion and conclusion are listed in Section IV.

2. Method

2.1 Problem definition

The coordinate transformation of a 3×1 vector \( \mathbf{x} \) between the sensor frame \( S \) and the inertial frame \( I \) is

\[
\mathbf{j} \mathbf{x} = \mathbf{j} \mathbf{R} \mathbf{s} \mathbf{x}
\]

where the left superscripts \( I \) and \( S \) of \( \mathbf{x} \) indicate that the vectors are observed in the inertial and sensor frame coordinates, respectively, and \( \mathbf{j} \mathbf{R} \) is the DCM of the sensor frame \( S \) with respect to the inertial frame \( I \). The DCM \( \mathbf{j} \mathbf{R} \) contains the three unit and orthogonal column vectors of the inertial frame observed in the sensor frame as

\[
\mathbf{j} \mathbf{R} = \begin{bmatrix} \mathbf{s} \mathbf{X}_I & \mathbf{s} \mathbf{Y}_I & \mathbf{s} \mathbf{Z}_I \end{bmatrix}^T
\]

Note that the proposed KF uses another frame \( I' \) which is tilted (rotated) about the y-axis by the dip angle \( \theta \) from the inertial frame \( I \). Here, the dip angle also known as magnetic inclination is the angle defined by the horizontal axis and the Earth’s magnetic field vector. The location-dependent dip angle is not zero except at the magnetic equator [14]. The relationship between \( I \) and \( I' \) is

\[
\mathbf{i} \mathbf{r} \mathbf{R} = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}
\]

where the dip angle can be determined as

\[
\theta = \cos^{-1} (\mathbf{s} \mathbf{Z}_I \cdot \mathbf{m}) - \pi/2.
\]

The proposed KF uses two reference vectors to determine orientation: one is the gravity vector \( \mathbf{g} \), which is aligned with \( \mathbf{s} \mathbf{Z}_I \), and the other is the local magnetic field vector \( \mathbf{m} \), which is aligned with \( \mathbf{s} \mathbf{X}_I \). Therefore, the reference vectors can be expressed as

\[
\mathbf{s} \mathbf{g} = \mathbf{g} \times \mathbf{s} \mathbf{Z}_I \quad \text{and} \quad \mathbf{s} \mathbf{m} = \mathbf{m} \times \mathbf{s} \mathbf{X}_I
\]

where \( \mathbf{s} = ||\mathbf{s}\| \) and \( m = ||\mathbf{m}\| \) (see Fig. 1). By considering the relationship of

\[
\mathbf{i} \mathbf{r} \mathbf{R} = \mathbf{i} \mathbf{r} \mathbf{R}^T \mathbf{i} \mathbf{r} \mathbf{R}
\]

the axis \( \mathbf{s} \mathbf{X}_I \) can be written as

\[
\mathbf{s} \mathbf{X}_I = \cos \theta \mathbf{X}_I - \sin \theta \mathbf{s} \mathbf{Z}_I.
\]

The DCM \( \mathbf{i} \mathbf{r} \mathbf{R} \) is then determined as follows: (i) \( \mathbf{s} \mathbf{Z}_I \) is estimated by utilizing \( \mathbf{s} \mathbf{g} \) from the accelerometer signal, (ii) \( \mathbf{s} \mathbf{X}_I \) is estimated by utilizing \( \mathbf{s} \mathbf{m} \) from the magnetometer signal and \( \mathbf{s} \mathbf{Z}_I \), and (iii) \( \mathbf{s} \mathbf{Y}_I \) is then estimated by orthogonalizing the unit vectors, i.e., \( \mathbf{s} \mathbf{Y}_I = \mathbf{s} \mathbf{X}_I \times \mathbf{s} \mathbf{Z}_I \). Henceforth, \( \mathbf{i} \mathbf{r} \mathbf{R} \), \( \mathbf{s} \mathbf{X}_I \), \( \mathbf{s} \mathbf{Y}_I \), and \( \mathbf{s} \mathbf{Z}_I \) are simply denoted as \( \mathbf{R} \), \( \mathbf{X} \), \( \mathbf{Y} \), and \( \mathbf{Z} \) for convenience.

![Fig. 1. Inertial and sensor frames, and dip angle](image-url)
2.2 Algorithm description

The proposed method uses two linear Kalman filters, consisting of an attitude KF (estimating roll and pitch) followed by a heading KF (estimating yaw). Herein, the attitude and heading are respectively represented by the Z-axis and X-axis unit vectors of DCM. In other words, while the first KF is applicable for the vertical axis of the inertial frame, the second KF is for the horizontal heading axis.

2.2.1 Sensor modeling

Sensor signals (y’s) from the gyroscope \((G)\), the accelerometer \((A)\), and the magnetometer \((M)\) are modeled, respectively, as follows

\[
y_G = s\omega + n_G \tag{7a}
\]

\[
y_A = sg + sa + n_A \tag{7b}
\]

\[
y_M = sm + sd + n_M \tag{7c}
\]

where \(\omega\) is the angular velocity, \(a\) is the external acceleration, \(d\) is the magnetic disturbance, and \(n\)’s are the measurement noise vectors. In (7b) and (7c), the external acceleration and the magnetic disturbance are modeled as a first order Markov chain process as in [10] and [16], i.e.,

\[
sa_t = ca_s a_{t-1} + e_{a,t} \tag{8a}
\]

\[
sd_t = cd_s d_{t-1} + e_{d,t} \tag{8b}
\]

where \(c_{a_s}\) and \(c_{d_s}\) are process constants, and \(e_{a,t}\) and \(e_{d,t}\) are the time-varying errors of the process models.

2.2.2 1st Step KF: Attitude estimation

The first KF is used to estimate \(sZ\) (which is the state vector of the first KF) based on [10]. The process model is based on the gyro measurements and is related to a strapdown integration in accordance with

\[
sZ_t = (1 - \Delta t\tilde{y}_{G,t-1})sZ_{t-1} + \Delta t \left(-s\tilde{Z}_{t-1}\right)n_G \tag{9}
\]

where \(\Delta t\) is the step size, and the overhead tilde “” is used to represent the standard vector cross product (i.e., \(\tilde{a} = [ax]\)). The measurement model is based on the accelerometer measurement, (7b). By considering (8a), it can be rewritten as

\[
y_{A,t} - ca_s a_{s,t} = g_s Z_t - sa_{s,t} + n_A \tag{10}
\]

where equations \(sa_{s,t} = sa_s - sa_{t-1}\) and \(sa_t = ca_s a_{t-1}\) are used. The minus and plus superscripts denote the \(a\) priori (or predicted) and the \(a\) posteriori (corrected) estimates, respectively.

From (9) and (10), the following KF equations are derived:

\[
sZ_t = \Phi_{1,t}^{-1} sZ_{t-1} + w_{1,t-1} \tag{11}
\]

\[
z_{1,t} = H_1 sZ_t + v_{1,t} \tag{12}
\]

where the transition matrix \(\Phi_t\) and process noise \(w_t\) are

\[
\Phi_{1,t} = I - \Delta t\tilde{y}_{G,t-1} \tag{13}
\]

\[
w_{1,t} = \Delta t \left(-s\tilde{Z}_{t-1}\right)n_G \tag{14}
\]

Moreover, the measurement vector \(z_{1,t}\), observation matrix \(H_1\), and the measurement noise \(v_{1,t}\) are

\[
z_{1,t} = y_{A,t} - ca_s a_{s,t} \tag{15}
\]

\[
H_1 = gI \tag{16}
\]

\[
v_{1,t} = s\tilde{a}_{s,t} + n_A \tag{17}
\]

The covariance matrices of the process and measurement noise vectors, \(Q_{1,t} = E[w_{1,t}w_{1,t-1}^T]\) and \(M_{1,t} = E[v_{1,t}v_{1,t}^T]\), are

\[
Q_{1,t} = -\Delta t^2 s\tilde{Z}_{t-1}\Sigma_{a} s\tilde{Z}_{t-1} \tag{18}
\]

\[
M_{1,t} = \Sigma_{acc1} + \Sigma_{a} \tag{19}
\]

where \(E\) is the expectation operator. Correspondingly, the covariance matrices of the gyro and accelerometer measurement noise vectors \((\Sigma_g\) and \(\Sigma_{a}\), respectively) are set to \(\sigma_g^2I\) and \(\sigma_a^2I\) (where \(\sigma_g^2\) and \(\sigma_a^2\) are the noise variances). In addition, the covariance matrix of the acceleration model error \(\Sigma_{acc1}\) is defined as \(E[(s\tilde{a}_{s,t})(s\tilde{a}_{s,t})^T]\), and is set to

\[
\Sigma_{acc1} = 3^{-1}c_{a_s}^2\left[a_{s,t}\right]\left[a_{s,t}\right]^T \tag{20}
\]

2.2.3 2nd Step KF: Heading estimation

The second KF is used to estimate \(sX\) (which is the state vector of the second KF). Similarly with (9), the process model is:

\[
sX_t = (1 - \Delta t\tilde{y}_{G,t-1})sX_{t-1} + \Delta t \left(-s\tilde{X}_{t-1}\right)n_G \tag{21}
\]

The measurement model is based on the magnetometer measurement, as indicated by (7c). However, it should be noted that while the gravity vector in the accelerometer signal (associated with the first KF) is aligned with the vertical axis, the Earth’s magnetic field vector in the magnetometer signal (associated with the second KF) is not aligned with the heading axis due to the dip angle. Therefore, the Earth’s magnetic field vector needs to be
projected to the heading axis. By considering (3) and (6), (7c) can be rewritten as

$$y_M = m \cos \theta \mathbf{Z} - m \sin \theta \mathbf{d} + n_M.$$  (22)

By applying $s \mathbf{Z}_{x,y} = s \mathbf{Z}_t^+ - s \mathbf{Z}_t$, $s \mathbf{d}_{x,y} = s \mathbf{d}_t^+ - s \mathbf{d}_t$, and $s \mathbf{d}_t = c_d s \mathbf{d}_{t-1}$, (22) becomes

$$y_{x,y} = m \sin \theta \mathbf{Z}_t^+ - c_d s \mathbf{d}_t^+ , \quad (23)$$

Note that the terms on the left-hand side of (23) are available at this stage since $s \mathbf{Z}_t^+$ and $\theta$ are determined at the first KF. Note also that since $s \mathbf{m}_t$ is not available, the dip angle $\theta$ — used in (23) — is obtained as

$$\theta = \cos^{-1}\left(\frac{s \mathbf{Z}_t^+ - s \mathbf{m}_t}{s \mathbf{d}_t}\right) - \pi / 2$$  (24)

where $s \mathbf{m}_t = y_M - s \mathbf{d}_t$.

From (21) and (23), the following KF equations are derived

$$s \mathbf{X}_t = \Phi \mathbf{X}_{t-1} + w_{x,t-1}$$  (25)

$$z_{x,y} = h_2^s \mathbf{X}_t + v_{x,y}$$  (26)

Where $\Phi_2 = \Phi_1$ and $w_{x,t-1} = \Delta(\mathbf{L}^{-1} \mathbf{X}_t) \mathbf{n}_a$. Furthermore,

$$z_{x,y} = y_{x,y} + m \sin \theta \mathbf{Z}_t^+ - c_d s \mathbf{d}_t^+$$  (27)

$$H_2 = m \sin \theta \mathbf{t}_h$$  (28)

The covariance matrix of the process noise $Q_{z_{x,y}}$ is

$$Q_{z_{x,y}} = \Delta(\mathbf{L}^{-1} \mathbf{X}_t) \Sigma_{z_{x,y}} \mathbf{L^{-1}} \Delta(\mathbf{L}^{-1} \mathbf{X}_t)^T$$

where $\Sigma_{z_{x,y}}$ is set to be equal to $\sigma_z^2 \mathbf{I}$ (where $\sigma_z^2$ is the noise variance), $\Sigma_{\text{acc}} = E\left[\left(s \mathbf{a}_{x,y}^+\right)^T \left(s \mathbf{a}_{x,y}^+\right)\right]$ and $\Sigma_{\text{m}} = E\left[\left(s \mathbf{d}_{x,y}^+\right)^T \left(s \mathbf{d}_{x,y}^+\right)\right]$. In the proposed method, $\Sigma_{\text{acc}}$ is set to be equal to $\Sigma_{\text{acc}}$, and $\Sigma_{\text{m}}$ is set to $2^2 \mathbf{J}_d^T \mathbf{J}_d \mathbf{I}$, similarly with $\Sigma_{\text{m}}$.

The overall structure of the proposed algorithm is illustrated in Fig. 2. Owing to the sequential KF structure, the effects of the magnetic disturbance are limited to the

![Fig. 2. Structure of the proposed sequential Kalman filter](image-url)

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attitude (i.e., roll and pitch) estimations, and do not involve any additional decoupling processes. This overcomes an inherent issue in quaternion-based estimation algorithms.

3. Result

3.1 Test setup

For the verification of the proposed algorithm, which was implemented using MATLAB programming, an MTw sensor (from Xsens Technologies B. V., Netherlands) was used as the input to the proposed algorithm operating at a 100 Hz sampling rate. Additionally, for the investigation of the estimation accuracy, an OptiTrack Flex13 camera motion capture system (from NaturalPoint, Inc. USA) was used to achieve truth reference of the orientation based on the spatial positions of three markers on a plane (see Fig. 3). The parameter values were set in the proposed algorithm to $c_a = 0.1$ and $c_d = 0.15$.

3.2 Test conditions

Four different tests were performed under varying conditions in terms of movement speed and magnetic disturbance. A steel plate with dimensions of $117 \times 225 \times 2.2 \text{ mm}^3$ was used to generate the magnetic disturbance. Test conditions are shown below.

**Test A**: Starting 50 cm away from the fixed steel plate (i.e., a magnetically undisturbed area), the MTw was moved closer to the plate. The sensor slowly hung around in the vicinity of the steel plate with continuous orientation changes for approximately 30 s. The sensor then moved back to its initial position.

**Test B**: It is similar to Test A. However, the sensor’s speed was faster, and the motion range was wider than that of Test A (see Fig. 4). Note that Fig. 4(a) shows the magnetic disturbance applied by the steel plate. The disturbance with respect to the inertial frame $^I \mathbf{d}$ was obtained in accordance to $^I \mathbf{d} = ^i \mathbf{R}_{opt} \mathbf{v} - ^m \mathbf{m}$ owing to the unavailability of $^n_M$, where $^i \mathbf{R}_{opt}$ is the truth reference orientation from the optical motion capture system.

**Test C**: MTw remained stationary (hence, ideally, the orientation should be unchanged), while the nearby plate was swayed back and forth along each axis intermittently for approximately 20 s.

**Test D**: It is similar to Test C. However, the plate’s motion was more arbitrary than that of Test C. More importantly, the duration of magnetically perturbed

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**Fig. 3.** Test setup: optical motion tracker and MTw inertial/magnetic sensor

**Fig. 4.** Test B results: (a) exposed magnetic disturbance for each axis, and (b)-(d) estimation errors with respect to the true reference
conditions was much longer (i.e., approximately 80 s) than the duration in Test C (see Fig. 5). The purpose of this test was to see how long the algorithm can maintain the estimation accuracy, and also how fast the algorithm can recover the performance after the disturbance disappears.

For each of the four tests, the orientation was estimated using three different methods. Method 1 is the DCM-based proposed algorithm. Method 2 is a quaternion-based algorithm presented in [9] by Madgwick et al. The open-source MATLAB® implementation algorithm is available at http://www.x-io.co.uk/open-source-imu-and-ahrs-algorithms/ (last accessed on October 2016). Method 3 is the black-boxed MTw’s algorithm, XKF-3w [17]. The estimation accuracy was evaluated in terms of root-mean-squared-error (RMSE) of the Euler angles.

### 3.3 Experimental Results

Table 1 shows the total average and individual Euler angle RMSE values estimated from three different algorithms for the four tests.

In Test A, Methods 1 and 3 produced accurate results (i.e., < 2° for any individual Euler angle), since the test conditions were not extreme in terms of motion speed and range. It can be seen that the yaw estimation based on Method 2 was affected more by the magnetic disturbance compared to other methods (i.e., 0.84° from Method 1 and 1.28° from Method 3 vs. 2.5° from Method 2).

In Test B, although the yaw estimations, based on Methods 1 and 3, were also affected by the severe test conditions of this test, the yaw estimation error based on Method 2 was considerably increased compared to other methods. Furthermore, it is noted that the roll estimation error reached values up to 30° when the yaw estimation error increased at approximately 14 s. It is also observed that when the magnetic disturbance shown in Fig. 4(a) was eliminated at 17 s, the yaw estimation accuracy of Method 2 recovered gradually, as shown in Fig. 4(d).

In Tests C and D, since the sensor remained stationary, the roll and pitch estimations were fairly accurate in all of the three tests. However, yaw estimations were affected by the magnetic disturbances. Let us compare the results of Test D with those of Test C. In the case of Methods 1 and 3, although the RMSE of the yaw estimation in Test D is larger than that of Test C (due to a longer exposure time to the disturbance), the RMSEs of the roll and pitch estimation in Test D are almost the same as those of Test C. This implies that Methods 1 and 3 can yield roll and pitch estimates that are unaffected by magnetic disturbances. On the contrary, in the case of the quaternion-based Method 2, Test D led to higher RMSEs not only in yaw but also in roll and pitch estimations, in comparison to Test C. This is because the roll and pitch information in the magnetometer signals are contained in the quaternion components. This can be clearly seen in Figs. 5(b) and 5(c).

Fig. 5. Test D results: (a) exposed magnetic disturbance for each axis, and (b)-(d) estimation errors with respect to the true reference.

Overall, Method 2 was severely affected by the disturbance, and Method 1 outperformed Method 3. This superiority of the results from Method 1 compared to the results from Method 3 in yaw estimation partly arises from the steady state error in the latter method. As shown in Fig. 5(d), while the estimation error from Method 3 was gradually decreased when the magnetic environment returned to a homogeneous condition, the recovery did not start just after the disturbance disappeared but approximately 10 s later. The recovery of Method 1 started immediately after the disturbance disappeared.
The patterns of yaw estimation errors are also different for Methods 1 and 3. While the yaw estimation error from Method 3 linearly increased during the prolonged exposure to the disturbance, a fluctuating pattern of variation was observed for Method 1.

4. Discussion and Conclusion

Given that the magnetic disturbances in the magnetometer signals are more problematic than the external acceleration in the accelerometer signals, quaternion-based orientation estimation algorithms have a critical drawback in that the disturbance could adversely affect both the yaw and the roll and pitch [18]. This effect can be observed in Figs. 5(b) and 5(c) where the quaternion-based algorithm, Method 2, produced erroneous roll and pitch estimations, while Methods 1 and 3 were unaffected by the magnetic disturbances in roll and pitch estimations.

Concerning Method 1, the aforementioned advantage of the proposed method arises from the sequential structure of the DCM-based KF, which is well paired with AHRS (i.e., attitude followed by heading estimation), rather than from a special treatment of magnetic disturbance (for example, via disturbance compensation mechanisms). In fact, Method 2 also has a magnetic disturbance compensation mechanism according to [9]. This prior work indicated that the magnetic disturbances only affect the estimated heading component of the orientation by using the compensation mechanism. Our results do not support these findings. We consider that Method 2 yields roll and pitch estimates that are unaffected from magnetic disturbances (but not in an absolute sense).

It is interesting to note that the roll and pitch estimated using Method 3 (MTw’s XKF-3w) were also unaffected by the disturbance. This finding correlates with the MTw’s manual specifications [17], which indicate that: “If the local Earth magnetic field is temporarily disturbed, XKF-3w will track this disturbance instead of incorrectly assuming there is no disturbance. However, in the case of structural magnetic disturbance (>10 to 20 s) the computed heading will slowly converge to a solution using the “new” local magnetic North. Note that the magnetic field has no direct effect on the inclination estimate.”

With regard to the dip angle related to Eq. (3), the proposed method updates it at every single timestep. In theory, the dip angle at a certain location is constant, which implies that the initially computed dip angle can be used for any timestep within the entire time interval. In practice, however, estimations based on the initial dip angle were not as accurate as the proposed method, e.g., the yaw RMSE of 4.20° of Test B based on the initial dip angle versus a value of 3.45° based on the updated dip angle.

Under the four different magnetically perturbed conditions, Method 1 produced a similar degree of accuracy compared to that from Method 3 (the state-of-the-art orientation algorithm employed by MTw). In our limited number of tests, Method 2 yielded relatively low levels of estimation accuracy. However, it should be noticed that Method 2 requires one adjustable parameter $\beta$ representing the gyroscope measurement error expressed as the magnitude of a quaternion derivative. The results shown in Table 1 are obtained when $\beta$ is set to 0.033. The same value was also selected for the verification tests in [9]. If an optimal parameter is selected for each of the considered tests, a lower RMSE is expected.

In this paper, a sequential DCM-based orientation KF for AHRS has been presented. The proposed algorithm uses two linear KFs, consisting of an attitude KF followed by a heading KF. In the latter case, the direction of the local magnetic field vector is projected onto the heading axis of the inertial reference frame by considering the dip angle, which can be determined after the attitude KF. In addition to the external acceleration model (that deals with kinematically perturbed conditions) in the attitude KF, the proposed algorithm adopts the magnetic disturbance model in the heading KF in order to deal with magnetically perturbed conditions.

Owing to the sequential KF structure, the effects of the magnetic disturbance are limited to the roll and pitch estimations, and do not involve any additional decoupling process. This overcomes the inherent issue in the quaternion-based estimation algorithms.

The proposed algorithm was evaluated under various magnetically perturbed conditions to investigate the estimation performance, depending on the kinematic and magnetic conditions. The averaged RMSE of the two dynamic tests (i.e., Tests A and B) was 1.71°, while that of the two static tests (i.e., Tests C and D) was 0.79°. This demonstrates a high-estimation performance of the proposed algorithm, even in magnetically inhomogeneous environments. Specifically, the proposed method outperforms the other two in terms of yaw estimation accuracy during perturbation and recovery speed.

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References


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