Pose Identification and Updating in Autonomous Vehicles

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***Abstract*—In this paper, a novel algorithm to know the pose of any autonomous vehicle is described. Such a system (Attitude and Heading Reference System, AHRS) is essential for real time vehicle navigation, guidance and control applications. For low funded projects, with simple sensors, efficient and robust algorithms become necessary for an acceptable performance, and the well-known extended Kalman filter (EKF) fulfills those requirements. In this kind of applications, the use of the EKF in direct configuration has been much less explored than its counterpart, the EKF in indirect configuration. Specifically, in this paper a novel method based on an Extended Kalman Filter in direct configuration is proposed, where the filter is explicitly derived from both kinematic and errors models. Experiments with real data show that the proposed method is able to maintain an accurate and drift-free attitude and heading estimation.**

Keywords—Attitude Estimation; Sensor Fusion; Vehicle Navigation.

I. INTRODUCTION

Autonomous Vehicle applications (Unmanned Ground Vehicles, Micro-Air Vehicles, Unmanned Aerial Vehicles (UAV), and Marine Surface Vehicles) all require accurate position and attitude to be effective [1]. While navigation grade Inertial Measurement Units (IMU) have existed for many years, they remain very expensive, and out of reach both in terms of cost and payload for all but the best funded projects. Small UAVs, even if the can afford the cost, cannot supply the necessary power to these units. A combination of instruments capable of maintaining an accurate estimate of the vehicle attitude, while it maneuvers, is called Attitude and Heading Reference System (AHRS). The first AHRS implementations were based only in gyroscopes. Gyros are prone to bias, which could produce large errors after long periods of integration. Filtering techniques are often required if less reliable (low-cost) gyros are used. Using filtering techniques, other sensors (i.e., accelerometers and magnetometers) can be combined with gyros in order to limit the attitude errors in time. With the availability of hardware (i.e., MEMS sensors and microcontrollers) several approaches for AHRS systems in the literature have been appearing, especially in the last decade. Nowadays, AHRS are typically based on gyros that are updated by gravity sensors (i.e., accelerometers) for pitch and roll and by magnetic field sensors for yaw. Nevertheless, depending on the application, it is common to find approaches relying in alternative sensors for bounding attitude errors in time, [2]-[5].

Several estimation techniques have been used for attitude determination. Schemes presented in [2] and [3] use Linear Filtering and Iterated least-squares methods, respectively. The linear Kalman filter (KF), commonly used for estimating the system state variables and for suppressing the measurement noise has been recognized as one of the most powerful state estimation techniques. Some methods relying on linear Kalman Filtering are presented in [5][6].

There are two basic ways for implementing the EKF: total state space formulation (also referred to as the direct formulation) and error state space formulation (also referred as the indirect formulation).

EKF in indirect formulation estimates a state vector which represents the errors between the estimated state and the estimated nominal trajectory. The measurement in the error state space formulation is made up entirely of system errors and is almost independent of the kinematic model. Most of the approaches follow this kind of configuration [4][7][8]. The differences among those methods mainly consist of variations in the design of the error models.

In EKF, in direct configuration the vector state is updated implicitly with the predicted state and the measurement residual (the difference between the predicted and current measurement). In this kind of EKF configuration, the system is essentially derived from the system kinematics. One of the characteristics of the direct configuration is its conceptual clarity and simplicity. In addition, it is possible to found other methods which rely in variations of Kalman filtering as the Unscented Kalman filtering [9]. Another interesting family of methods for attitude estimation is the nonlinear observers [10], but unsuitable for this research due to high computation load and real time purposes.

In a previous work [11], an uncoupled approach is presented. In that method, an EKF in direct configuration derived from the kinematic model estimates the attitude of the device, whereas an extra KF derived from the error sensor model estimates the gyro bias. However, the main drawback for the previous architecture was not to use optimally the full information available in the system covariance matrix. These data are useful to make a finest estimation of the system errors. As a consequence, some parameters had to be artificially tuned in order to improve the performance of the method.

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This paper describes a novel algorithm for implementing an Attitude and Heading Reference System based on an Extended Kalman Filter in direct configuration. In this approach, the filter is explicitly derived from both the kinematic and error models. One of the advantages of the proposed approach is due to the clarity and simplicity associated with the implementation of the EKF in direct configuration. Section II describes the proposed method and the novel system architecture. Results with real data are presented in Section III, and some conclusions and future work are presented at the end of the paper.

II. METHOD DESCRIPTION

A. Vector state and system specification

The goal of the proposed method is the estimation of the following system state $\hat{x}$:

$$\hat{x} = \begin{bmatrix} q^{nb} & \omega^b & x_g \end{bmatrix}' \quad (1)$$

where $q^{nb} = [q_1,q_2,q_3,q_4]$ is a unit quaternion representing the orientation (roll, pitch and yaw) of the body (device); $\omega^b = [\omega_x\ \omega_y\ \omega_z]$ is the bias-compensated velocity rotation of the body expressed in the body frame; $x_g = [x_{g\_x}\ x_{g\_y}\ x_{g\_z}]$ is the bias of gyros.

In this work, the axes of the coordinate systems follow the North, East, Down (NED) convention. For simplicity, the orientation of the body follows Euler angles α, β and γ denoting respectively roll, pitch and yaw, respectively. Euler angles can be computed from quaternion q^{nb}.

In order to estimate the system state $\hat{x}$, measurements obtained with an IMU of 9-DOF are considered. The IMU is formed by a 3-axis gyroscope, a 3-axis accelerometer, and a 3-axis magnetometer.

1) Gyroscope measurements

The angular rate ω^b of the vehicle, measured by the gyros (in the body frame) and indicated as y_g, can be modeled by:

$$y_g = \omega^b + x_g + v_g \quad (2)$$

where x_g is an additive error (bias) and v_g is a Gaussian white noise with power spectral density (PSD) σ_g^2.

2) Accelerometer measurements

The acceleration of the device a^b, measured by the accelerometers (in the body frame) as y_a, can be modeled by:

$$y_a = a^b - g^b + x_a + v_a \quad (3)$$

where g^b is the gravity vector expressed in the body frame, x_a is an additive error (bias), and v_a is a Gaussian white noise with PSD σ_a^2. Bias in accelerometers triads are often relatively small, thus in this work it is neglected.

Magnetometer measurements: The earth field m^b measured (in the body frame) as y_m can be modeled by:

$$y_m = m^b + x_m + v_m \quad (4)$$

where v_m is a Gaussian white noise with PSD σ_m^2. Magnetometer bias x_m could be fairly large but extremely slow time varying; therefore in this work it is not considered for online estimation; instead a calibration technique, as the presented one in [10], could be used for setting its initial value.

B. Architecture of the system

Figure 1 shows the architecture of the system which is defined by the typical loop of prediction-update steps in the EKF in direct configuration:

System Prediction: Prediction equations propagate along the time the estimation of the system state, by means of the measurements obtained from gyroscopes. Prediction equations offer correct estimates at high frequency, but only for a short period of time.

System Update: The unavoidable small errors in gyro readings produce large errors in attitude estimation after long periods of integration. The use of aiding sensors capable of measuring external references becomes essential in order to limit the estimation error. In this work, the gravity vector *g* and the magnetic earth field *m* are used as external references for correcting roll, pitch and yaw estimations:

i) During the periods when the device is in a non-accelerating mode (variable rate), information about the attitude of the device-vehicle (roll and pitch) is incorporated into the system by means of the observation of the gravity vector.

ii) Information about the heading (yaw) of the device-vehicle is incorporated into the system (at a predefined constant rate) by means of the observation of the earth magnetic field.

System Prediction: At every step *k*, when gyroscope measurements are available, the system state $\hat{x}$ is updated by the following (discrete) nonlinear model.

$$\begin{cases} q^{nb}_{(k+1)} = \left(\cos\left(\|w\|\right) I_{4\times4} + \dfrac{\sin\left(\|w\|\right)}{\|w\|} W \right) q^{nb}_{(k)} \\ \omega^b_{(k+1)} = -\left(y_{g(k)} - x_{g(k)} \right) \\ x_{g(k+1)} = (1\text{-}\lambda_{xg}\Delta t) x_{g(k)} \end{cases} \quad (5)$$

In the model represented by (5), a closed form solution of $\dot{q} = 1/2(W)q$ is used for integrating the current bias-compensated velocity rotation ω^b over the quaternion q^{nb}. In this case $w = [\omega^b_{(k+1)}\Delta t/2]'$ and:

$$W = \begin{bmatrix} 0 & -w_1 & -w_2 & -w_3 \\ w_1 & 0 & -w_3 & w_2 \\ w_2 & w_3 & 0 & -w_1 \\ w_3 & -w_2 & w_1 & 0 \end{bmatrix} \quad (6)$$

Also an alternative kinematic model for modeling the orientation of a camera by a quaternion can be found in a previous authors' work, [12]. Parameter λ_{xg} is a correlation time factor which models how fast the bias of gyro is varying. Δt is the sampling time of the system.

The state covariance matrix *P* is taken a step forward by:

$$P_{(k+1)} = \nabla F_x P_{(k)} \nabla F_x' + \nabla F_u U \nabla F_u' \quad (7)$$

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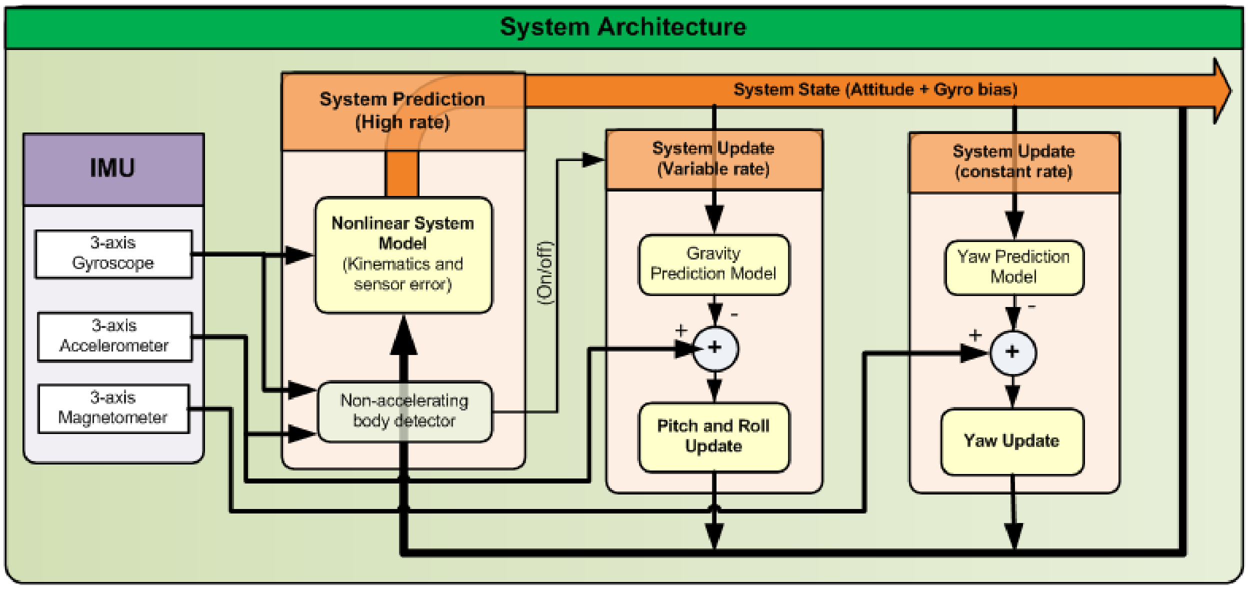

Figure 1. System architecture defined by an EKF in direct configuration.

The measurement noise of gyroscope v_g is incorporated into the system by means of the process' noise covariance matrix U, through parameter σ_g^2:

$$U = diag\left[\sigma_g^{\ 2} I_{3\times3} \quad \sigma_{xg}^{\ 2} I_{3\times3}\right] \tag{8}$$

The full model used for propagating the sensor bias error is: $bias_{k+1}=(1-\lambda\Delta t)bias_k + v_b$, where v_b models the uncertainty in the bias drift. The uncertainty in bias for gyro v_{xg} is incorporated into the system through the noise covariance matrix U via PSD parameter σ_{xg}^2.

$$\nabla F_x = \begin{bmatrix} \frac{\partial fq^{nb}}{\partial q^{nb}} & \frac{\partial fq^{nb}}{\partial \omega^{b}} & 0 \\ 0 & 0 & \frac{\partial f\omega^{b}}{\partial x_g} \\ 0 & 0 & \frac{\partial fx_g}{\partial x_g} \end{bmatrix} \quad \nabla F_u = \begin{bmatrix} 0 & 0 \\ \frac{\partial f\omega^{b}}{\partial y_g} & 0 \\ 0 & \frac{\partial fx_g}{\partial v_{xg}} \end{bmatrix} \tag{9}$$

The Jacobian ∇F_x is formed by the partial derivatives of the nonlinear prediction model, (5), with respect to the system state $\hat{x}$. In Jacobian notation, "$\partial fx/\partial y$" is used for partial derivatives and it must be read as the partial derivative of the function f (which estimates the state variable x) with respect to the variable y. Jacobian ∇F_u is formed by the partial derivatives of the nonlinear prediction model, (5), with respect to the system inputs.

A. System Updates

The filter can be updated as follows:

$$\hat{x}_k = \hat{x}_{k+1} + W(z_i - h_i) \tag{10}$$

$$P_k = P_{k+1} - W S_i W' \tag{11}$$

where z_i is the current measurement and $h_i = h(\hat{x})$ is the predicted measurement; W is the Kalman gain computed from:

$$W = P_{k+1} \nabla H_i' S_i^{-1} \tag{12}$$

S_i is the innovation covariance matrix:

$$S_i = \nabla H_i P_{k+1} \nabla H_i' + R_i \tag{13}$$

∇H_i is the Jacobian formed by the partial derivatives of the measurement prediction model $h(\hat{x})$ with respect to the system state $\hat{x}$. R_i is the measurement noise covariance matrix. Equations (10) to (13) will be used for system updates together with the proper definitions of z_i, h_i, ∇H_i and R_i.

1) Roll and pitch updates

If the device is not accelerating, (i.e., $a^b \approx 0$), then (3) can be approximated as $y_a \approx -g_b + v_a$ (x_a is neglected). In this situation, accelerometer measurements y_a provide noisy observations about the gravity vector (in the body frame). The gravity vector g is used as an external reference for correcting roll and pitch estimations.

In order to detect the time (corresponding to k instants) that the body is in a non-accelerating mode, the Stance Hypothesis Optimal Detector (SHOE) is used [13].

The gravity vector g is predicted to be measured by the accelerometers as h_g:

$$h_g = R^{nb} \begin{bmatrix} 0 \\ 0 \\ g_c \end{bmatrix} \tag{14}$$

where g_c is the gravity constant and R^{nb} is the navigation to body rotation matrix computed from the current quaternion q^{nb}.

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If the device is not accelerating and a minimum period (corresponding to t_1 seconds) have elapsed since the last roll and pitch update, then the filter is updated (using (10) to (13)) with:

$$z_i = y_a \quad h_i = h_g \quad R_i = \mathrm{I}_{3\times3}\sigma_a^{\ 2} \quad \nabla H_i = \partial h_g / \partial \hat{\mathrm{x}} \qquad (15)$$

1) Yaw updates

The model h_γ used for predicting the heading (yaw) of the device is defined as:

$$h_\gamma = \mathrm{atan2}\left(2(q_2 q_3 - q_1 q_4), 1 - 2(q_3^{\ 2} + q_4^{\ 2})\right) \qquad (16)$$

where q^{nb}=[q_1,q_2,q_3,q_4] is the current quaternion; `atan2` is a two-argument function that computes the arctangent of y/x given y and x, within the range [-π, π].

As it can be observed in (16), the model does not predict the earth magnetic field to be measured. Instead, the model directly predicts the yaw angle to be measured. The idea of the selection of this measurement prediction model is due to the scalability of the system. In this sense, an alternative measurement device could be directly attached to the AHRS in order to correct the heading estimations.

In order to use the proposed measurement prediction model h_γ in the 3-axis magnetometer which is included in the 9-DOF IMU, a yaw measurement z_γ^n is obtained from the measured magnetic field y_m.

Due to the angle of inclination of the magnetic field vector, the measured magnetic vector is first projected to the north-east plane, by removing its z component:

$$m^n = R^{bn} y_m \qquad (17)$$

$$m_1^{\ n} = [m_x^{\ n} \quad m_y^{\ n} \quad 0] \qquad (18)$$

where m^n=[m_x^n, m_y^n, m_z^n] and R^{bn} is the body to navigation rotation matrix computed from the current quaternion q^{nb}. The magnetic field vector $m^n{}_1$ (expressed in the navigation frame), from which the z component has been removed, is projected back to the body frame by:

$$m^b = R^{nb} m^n{}_1 \qquad (19)$$

where m^b=[m_x^b, m_y^b, m_z^b] and R^{nb} is the navigation to body rotation matrix computed from the current quaternion q^{nb}. Finally, the measured yaw z_γ^n is obtained by:

$$z_\gamma^{\ n} = \mathrm{atan2}\left(-m_y^{\ b}, m_x^{\ b}\right) \qquad (20)$$

In this work it is assumed that the angle of declination of the magnetic field is ignored or is previously known. Measurements z_γ^n are assumed to be corrupted by Gaussian white noise v_γ with PSD σ_γ^2.

At constants intervals of t_2 seconds the filter is updated (using (10) to (13)) with:

$$z_i = z_\gamma^{\ n} \quad h_i = h_\gamma \quad R_i = \sigma_\gamma^{\ 2} \quad \nabla H_i = \partial h_\gamma / \hat{\mathrm{x}} \qquad (21)$$

III. EXPERIMENTAL RESULTS

In order to validate the performance of the proposed method, a comparative study with real data is presented. In this case, the output estimated by the proposed algorithm (Direct method) is compared with the output obtained from the method described in [14], which is based in an EKF in indirect formulation (Indirect method). For the comparative study, the output obtained from a commercial 3DM-GX3®45 AHRS unit is considered as the ground truth. This unit can be easily mounted in any ground vehicle.

For each test the 3DM-GX3®45 was randomly gyrate while it was held in a hand. At the same time, raw data obtained from the accelerometers, gyroscopes and magnetometers included in the unit, along with the attitude computed by the same unit, were recorded in a plain text file at a frequency of 100 Hz. Several data captures were carried out trying to cover different dynamic circumstances like periodic and soft turns as well as random and strong shakes. Each capture lasts about 3 minutes.

A MATLAB© implementation of both, the proposed approach (Direct method), as well as the Indirect method were executed in off-line mode, using the raw sensor data stored in the plain text files as input signals. The execution time was: i) Direct method = 736 microseconds/step, ii) Indirect method = 586 microseconds/step. It is important to note that for the Indirect method the size of the system state is 6 (actual rotational velocity is not included), instead of 9. So (as is typical in EKF applications) difference in execution time should be mostly related with the size of the system state.

The outputs obtained with: i) the Direct method, ii) the Indirect method and iii) the 3DM-GX3®45 unit have been compared. In experiments the mean absolute error (MAE) was used for comparing the performance of both methods:

$$\mathrm{MAE} = \frac{1}{n}\sum_{k=1}^{n} \left\| f_k - y_k \right\|$$

where n is the number of samples, f_k is the angle measured by the 3DM-GX3®45 unit at instant k, and y_k is the angle estimated by a method at instant k. In experiments, for clarity purposes, Euler angles are obtained every time that they are needed from the current estimated quaternion q^{nb}.

For the comparative study two aspects were evaluated:

a) The performance of the methods for estimating the gyro bias x_g. That is, the ability of the filters to converge when the initial conditions differ considerably from the actual value, in order to minimize the error in estimations.

b) The performance of the methods when the frequency of operation is reduced (or the sample time is increased).

For the case (a), the methods were executed over the input signals stored in the plain text files. After that, the methods were run again over the same input signals, but artificially introducing a huge extra bias $\mathrm{x}_{g(a)}$ into each gyro measurement y_g, so that: $y_g = \omega^b + \mathrm{x}_g + v_g + \mathrm{x}_{g(a)}$, see (2). In experiments $\mathrm{x}_{g(a)}$ = [.05 -.05 .025] radians.

For the case (b), the methods were first executed over all the samples captured. After this operation, the methods were executed again but in this case periodically skipping samples in order to emulate different frequencies of operation. In this case, 100Hz, 50Hz and 25Hz were considered.

Table I shows the average MAE obtained with the Direct method and the Indirect method for several captures of data (considering all the conditions previously described). As it can be appreciated, the computed MAE is in general very

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similar for both methods. In a more detailed observation, the Direct method performs slightly better for converging (and thus minimizing the error in estimation) when an initial huge gyro bias is present. On the other hand, the Indirect method shows a slightly better response at very low frequency of operation.

Figure 2 shows the progression over time for the estimations obtained with the Direct and the Indirect methods, for a test with random turns and strong shakes. The plots correspond to the response of both methods when an extra gyro bias and a frequency of operation of 100Hz are considered. In Figure 2, at the beginning of the test (before second 30th) it can be clearly appreciated the adverse effect in the estimated roll, pitch and yaw due to the integration of the contaminated gyro measurements (observe the absolute error corresponding to this period). However, the estimated gyro bias rapidly converges to its actual value due to the system updates carried out in the filters. When the gyro bias is estimated then the absolute error is minimized. For this test, also it can be appreciated that the convergence of the Direct method is faster than the Indirect Method, thus accelerating the minimization of errors estimation.

TABLE I
MEAN ABSOLUTE ERROR (DEGREES)

No extra bias	**100Hz**	**50 Hz**	**25 Hz**
Roll (Direct)	0.65	0.84	2.62
Roll (Indirect)	0.66	0.83	2.50
Pitch (Direct)	0.36	0.58	1.80
Pitch (Direct)	0.35	0.56	1.74
Yaw (Direct)	0.68	0.96	2.42
Yaw (Indirect)	0.81	1.02	2.10
Extra Bias	**100Hz**	**50 Hz**	**25 Hz**
Roll (Direct)	1.12	1.28	3.01
Roll (Indirect)	1.39	1.54	2.92
Pitch (Direct)	0.87	1.07	2.30
Pitch (Direct)	0.98	1.19	2.33
Yaw (Direct)	2.52	3.52	5.76
Yaw (Indirect)	3.10	3.33	5.21

IV. CONCLUSION AND FUTURE WORK

This work presents a practical method for implementing an attitude and heading reference system that can applied to autonomous vehicles for an automatic navigation. The architecture of the system is based on an Extended Kalman filtering approach in direct configuration. Experiments with real data show that the proposed method is able to maintain an accurate and drift-free attitude and heading estimation. Moreover, it is capable of estimating the parameters of sensors error (i.e., gyro bias) in a robust manner, thereby improving the system estimations even when the quality of the measurements obtained from gyros is very poor. Therefore, the accuracy of the estimates is almost only limited by the pre-calibration of accelerometers and magnetometers. Based on the experimental results, it is considered that the method is enough robust for its use along with low-cost sensors. The modularity of the proposed architecture permits the scalability of the system. In such a case, an alternative measurement device could be easily attached to the system (replacing the magnetometers) in order to correct the heading estimations.

The EKF in general is not an optimal estimator (owned to its linearization nature). In addition, if the process is modeled incorrectly, the filter may quickly diverge. Also, it has been seen that the EKF tends to underestimate the true covariance matrix and therefore the filter could become inconsistent.

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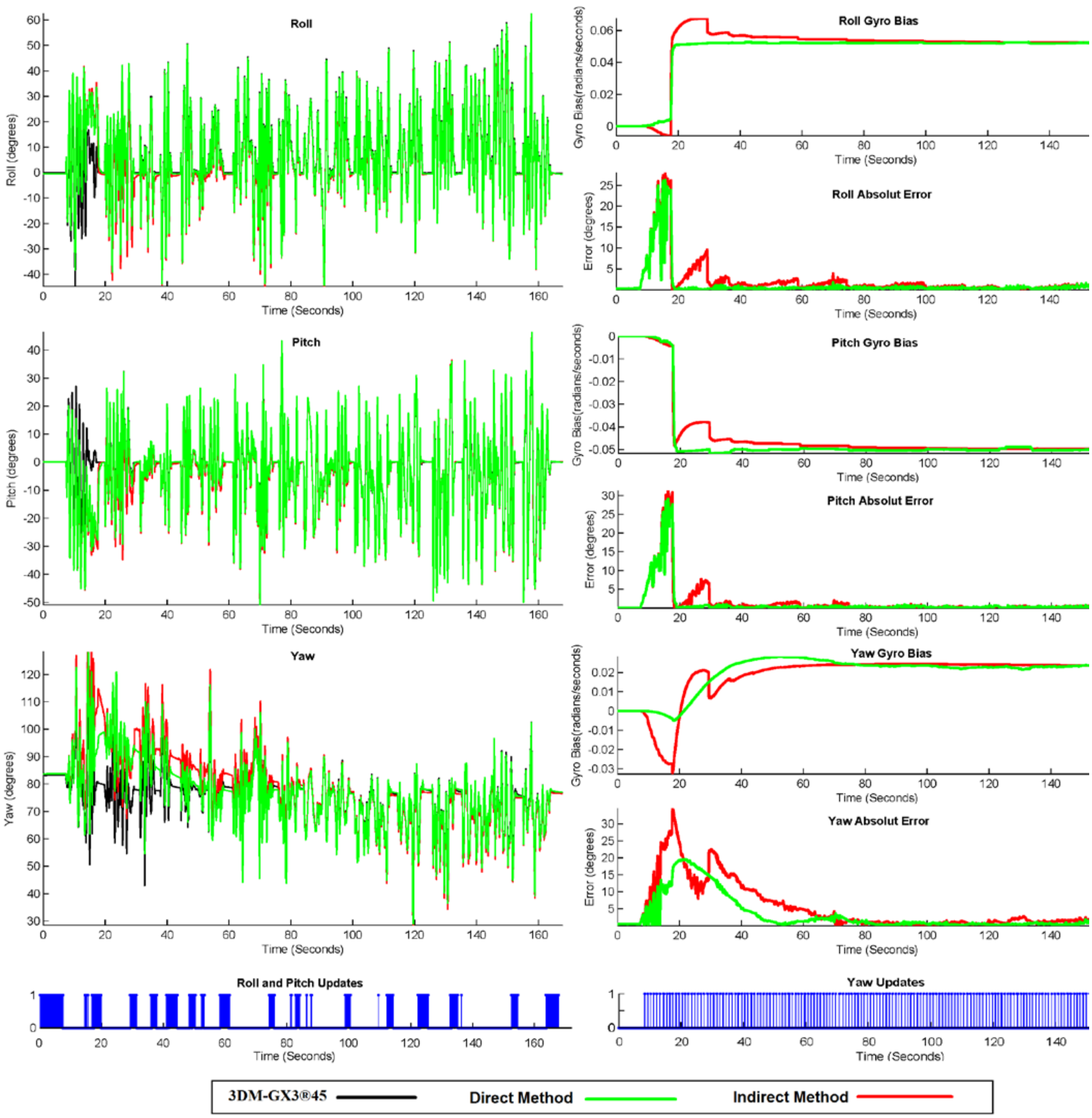

Figure 2. Estimation results for a test with random turns and strong shakes with a duration about 170 seconds.