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MULTI-SENSOR DATA FUSION FOR NAVIGATION

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Abstract. *In the present work a Multi-Sensor Data Fusion model is proposed to extract position and orientation of a frame from an Inertial Measurement Unit (IMU) and a Global Positioning System (GPS) for agricultural applications. Compare to other works in which the integration of the sensors occurs in different steps, in this work the sensor fusion is performed in a single stage, containing the equations of inertial navigation defined according to the adopted referential system, allowing to maximize the use of redundant data among the sensors. The system also includes a data preprocessing stage to filter the frequencies admitted essentially as noise in the project. This work demonstrates the feasibility of using low cost sensors to assist in problems of position and orientation estimation.*

Keywords: *Multi-sensor data fusion, Extended Kalman Filter, Inertial Measurement Unit, Global Positioning System.*

1. INTRODUCTION

Inertial navigation systems (INS) are characterized by a process in which the measurements made by sensors, such as gyroscopes and accelerometers, allow to estimate the position and orientation of a frame, or vehicle in which the system is installed, using laws of classical mechanics. Such laws predict that measured forces produce a proportional acceleration to the body, allowing to estimate speed and position of the body through a process of mathematical integration of acceleration with respect to the time (Titterton, 1997). IMUs based on micro electromechanical systems (MEMS) are found in INS applications due to their reduced cost when compared to high-end IMUs. However, such devices have a relatively lower accuracy and greater systematic errors, such as bias, scale factor and drift (Lou et al., 2011). Global navigation systems (GNSS), such as GPS, are also frequently adopted in navigation problems. These systems have the advantage of offering absolute position estimate, however, GPS modules typically offer lower refresh rates, as well as being affected by satellite orientation and interference from obstacles such as trees and buildings (Shen et al., 2007). In order to deal with these difficulties, in this research a sensor fusion model was proposed based on the integration between inertial sensors and GPS. The focus is to develop a navigation system for agricultural applications with the ability to estimate not only position and speed of the body as in many commercial solutions, but also its three-dimensional orientation.

The inherent errors of the sensors are composed of a deterministic and a stochastic part. The deterministic portion includes constant biases, scale factor and misalignment, which can be modeled and removed from the measurement by means of a calibration process. The stochastic portion is characterized by random errors such as Angle Random Walk (ARW), bias stability and Rate Random Walk (RRW) which cannot be removed and should be modeled by a stochastic process (Rasoulzadeh and Shahri, 2016). Particularly in navigation systems characterized by the integration of inertial systems with other sensors, the Kalman Filter (KF) is presented as an efficient solution for data fusion, allowing to combine the redundant information contained in the measurements to extract the optimum navigation solution (Brown, 1997).

2. MATERIALS AND METHODS

The basic principle of the proposed Multi-Sensor Data Fusion is shown in Fig. 1. The geodetic coordinates provided by the GPS module are transformed into local coordinate system North-East-Down (NED). The NED position coordinates and IMU data are filtered using Finite Impulse Response (FIR) filters in order to remove the frequency bands which have been empirically defined as noise. Finally, the data is combined through the Extended Kalman Filter (EKF).

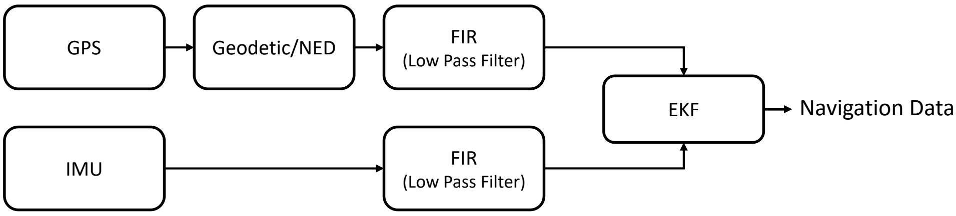

Figure 1. Multi-Sensor Data Fusion flowchart.

The defined FIR Filter consists of a 10^{th} order lowpass filter with cutoff frequency of approximately 13.4 Hz. To set this parameter, the cutoff frequency was gradually reduced to the point where signals sampled in the experiment were not degraded and the noise was partially reduced. The filter response is shown in Fig. 2.

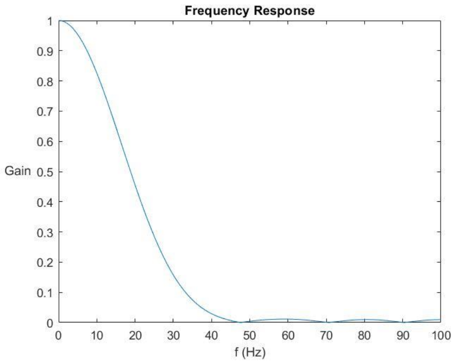

Figure 2. FIR filter response.

2.1 Coordinate system

The NED system consists of a local coordinate system fixed on Earth whose origin is normally established in the frame initial position. By convention the index n is added to the axes, where the X_n axis is oriented in the geographic north direction, the Y_n axis is oriented eastwards and the Z_n axis is oriented in the normal direction of the reference ellipsoid, according to Fig. 3 (Jekeli, 2001).

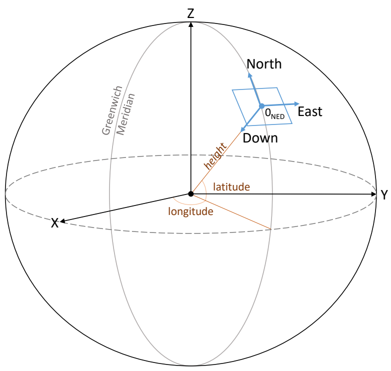

Figure 3. NED coordinate system.

The mathematical formality used in the transformation of the geodesic coordinate system (WGS84), which is the default for GPS used, into the NED system is explained as follows. Given a point P_g in geodesic coordinates (latitude φ, longitude λ and height h), as in Eq. (1), the coordinates in the Earth-Centered Earth-fixed system (ECEF) can be obtained by means of Eq. (2).

$$P_g = \begin{bmatrix} \varphi \\ \lambda \\ h \end{bmatrix} \tag{1}$$

$$P_e = \begin{bmatrix} x_e \\ y_e \\ z_e \end{bmatrix} = \begin{bmatrix} (N_e + h)\, cos\varphi\, cos\lambda \\ (N_e + h)\, cos\varphi\, sin\lambda \\ [N_e(1 - e^2) + h]\, sin\varphi \end{bmatrix} \tag{2}$$

Where e is the first eccentricity and N_e is the prime vertical radius of curvature as defined in WGS84.

The transformation of the ECEF coordinate system into NED coordinate system can be performed according to Eq. (3).

$$P_n = R_{n/e}\left(P_e - P_{e,ref}\right) \tag{3}$$

Where $P_{e,ref}$ is the origin of NED system in the ECEF coordinate system end $R_{n/e}$ is the rotation matrix from ECEF system to NED system.

2.2 Extended Kalman Filter

The Kalman Filter is an optimal recursive data processing algorithm that estimates the current state of a linear dynamic system using measurements linearly related to the state but corrupted by white noise. (Grewal and Andrews, 2001). Particularly, the Extended Kalman Filter consists of a linearization method of non-linear model from a current system state. This method is valid as long as it is possible to ensure a small linearization error for each update cycle, which can be achieved using relatively high refresh rates (Deilamsalehy and Havens, 2016). The EKF algorithm consists of prediction and update steps, as shown in Fig. 4. In the prediction step an estimation of the states and error covariance is performed for the next instant k. On the other hand, in the update step a new observation of states is performed, allowing to correct the Kalman Gain to improve the estimation of the next iteration (Welch and Bishop, 2001). The equations for the prediction and update step are presented respectively in Tab. 1 and Tab. 2.

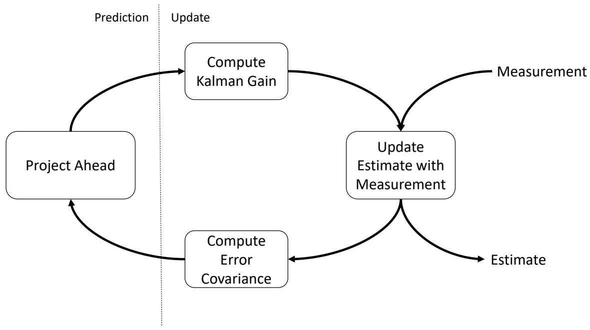

Figure 4. EKF algorithm.

Table 1. EKF prediction equations.

Predicted State Vector	$\hat{X}_k^- = f\left(\hat{X}_{k-1}\right)$
Predicted Error Covariance	$P_k^- = A_k P_{k-1} {A_k}^T + Q$

Table 2. EKF update equations.

Kalman Gain	$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$
State Vector	$\hat{X}_k = \hat{X}_k^- + K_k\left(Z_k - h\left(\hat{X}_k^-\right)\right)$
Error Covariance	$P_k = P_k^- - K_k H P_k^-$

The variable X is the state vector, A is the state transition matrix and H is the measurement matrix. The parameters Q and R are the process noise covariance and measurement noise covariance matrices, respectively.

2.3 Navigation equations

To model the error of the acceleration and angular velocity sensors a bias vector was established for each sensor as a random process and assumed noise as a zero-mean white gaussian signal. In this way, the true and measured values for the respective sensors can be correlated by the following Eq. (4) and Eq. (5).

$$a_n = R_f^n (f_{p,m} - b_a - n_a) + \vec{g} \tag{4}$$

$$\omega = \omega_m - b_\omega - n_\omega \tag{5}$$

The vectors a_n and ω are respectively the acceleration of the body in the NED coordinate system and its angular velocity. The specific force and angular velocity measured were represented by $f_{p,m}$ and ω_m. The matrix R_f^n performs the rotation of the frame coordinate system to the NED coordinate system. The vectors b_a and b_ω are the biases, n_a and n_ω are the noise and $\vec{g}$ is the gravity vector.

The state vector X for the proposed fusion model was defined according to Eq. (6).

$$X = [P_n \quad V_n \quad q_f \quad f_p \quad \omega \quad b_a \quad b_\omega] \tag{6}$$

Where, P_n is the position and V_n is the velocity of the frame in the NED system, q_f is the rotation quaternion that represents the orientation of the frame. The vectors f_p and ω are respectively the specific force and the angular velocity. The extra vectors b_a and b_ω correspond respectively to the biases of the accelerometer and the gyroscope.

From the state vector, the navigation equations are defined according to Tab. 5.

Table 5. Navigation Equations.

Velocity	$V_n = \frac{dP_n}{dt}$
Acceleration	$a_n = R_f^n f_p + \vec{g}$
Variation of the rotation quaternion	$\frac{dq_f}{dt} = \frac{1}{2}\Omega_\omega q_f$
Variation of the Specific Force	$\frac{df_p}{dt} = 0$
Variation of the Angular Velocity	$\frac{d\omega}{dt} = 0$
Variation of acceleration bias	$\frac{db_a}{dt} = 0$
Variation of angular velocity bias	$\frac{db_\omega}{dt} = 0$

The first equation consists of the velocity estimate from the derivative of the frame position in the NED coordinate system. The next equation consists of the acceleration in the NED coordinate system calculated based on the specific force of the body. The equation of variation of the rotation quaternion was obtained using the matrix Ω_ω that correlates the angular velocity and the rate of change in quaternion. In the proposed model the specific force and angular velocity of the body were defined as constant, as well as the biases assigned to the respective sensors.

2.4 Experimental Setup

The GPS module used in the experiments consists of the GY-NEO6MV2 model based on sensor NEO-6M u-blox. The module has horizontal accuracy of 2.5 m, maximum refresh rate of 10 Hz and maximum operating speed of 500 m/s. For the inertial measurements the IMU MinIMU-9 V3 manufactured by STMicroelectronics was used. The module consists of a tri-axial set of accelerometer, gyroscope and magnetometer. The sensors were configured for the 100 Hz refresh rate. To carry out the experiments the sensors were fixed inside a plastic box and connected through generic connectors to a development board Texas Instruments EK-TM4C1294XL. A C program has been implemented on the board to send sensor data through a USB port to a laptop and a MATLAB script was developed to receive the data and store it on computer's hard drive. The setup is shown in Fig. 5.

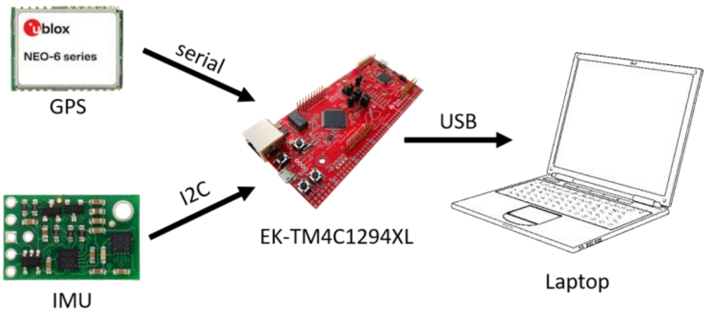

Figure 5. Experimental setup.

3. RESULTS

To validate the sensor fusion model, first a simulation was performed using the motion equations to emulate the sensors. Afterwards, an experiment was performed using the data obtained in a trajectory established in the Campus of São Carlos - Area 2 of the University of São Paulo (USP). The experiments are detailed below.

The first experiment consists of simulating a uniformly accelerated rectilinear motion with acceleration of 10 m/s^2 and a uniform circular motion with an angular velocity of 2 rad/s and a radius of 5 m. In order to produce the input data of the fusion system, the actual sensor noise was measured by keeping sensors at rest. Then, the variance obtained for each sensor was used in conjunction with the motion equations to emulate the sensor data in the respective movements. The obtained variances are presented in Tab. 6. These data were also used as parameters for the EKF covariance matrix R. The other parameters of the filter were established empirically. The results obtained by the sensor fusion algorithm are illustrated in the Fig. 6 and Fig. 7. The standard deviation obtained for each element of the state vector is shown in Tab. 7.

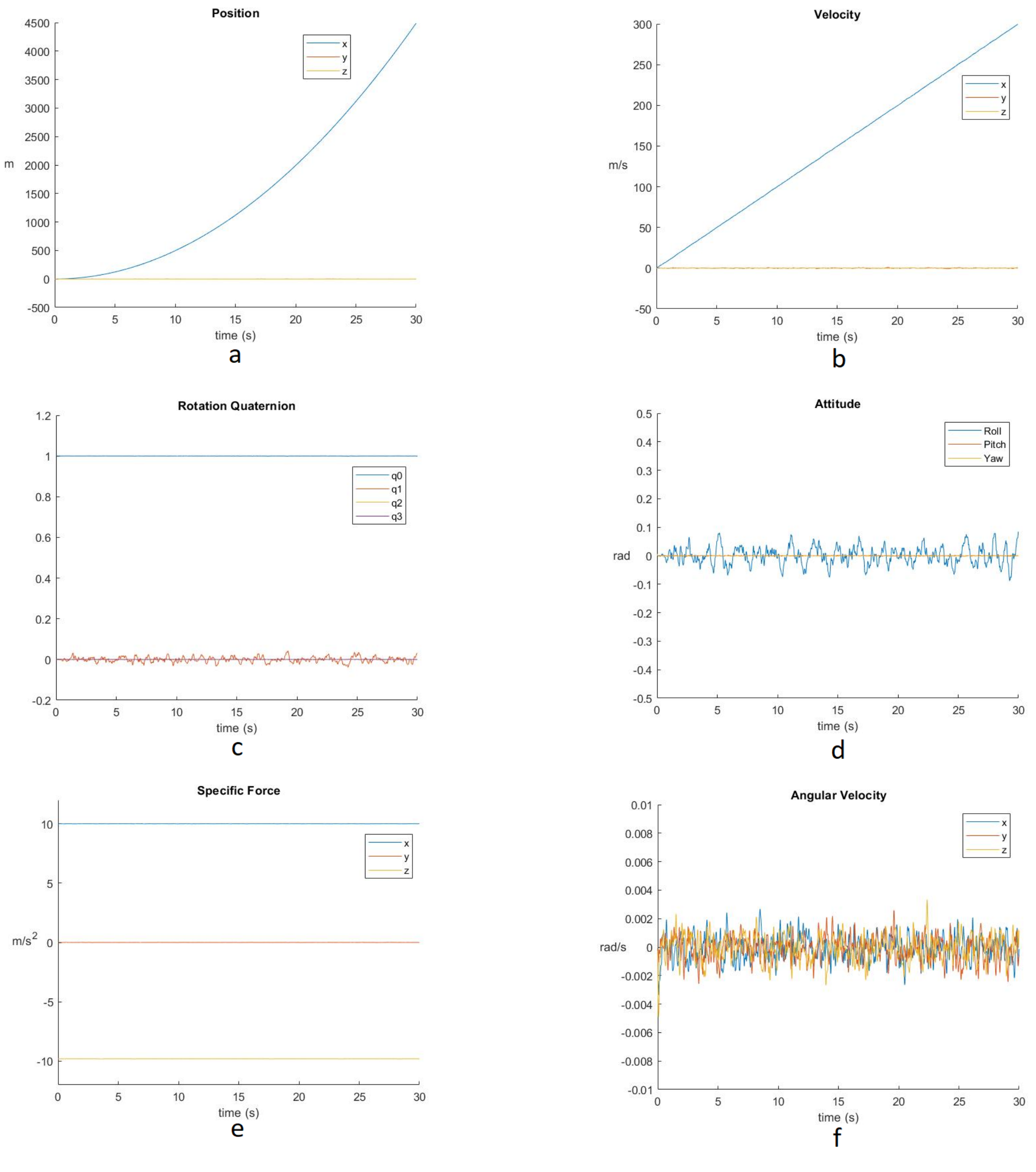

Figure 6. Simulation results of multi-sensor data fusion for uniformly accelerated rectilinear motion: (a) position; (b) velocity; (c) rotation quaternion; (d) attitude; (e) specific force; (f) angular velocity.

Table 6. Real variance for the sensors at rest.

	Variance	Units
GPS	0.496	m^2
Accelerometer	226.2×10^{-6}	$(m/s^2)^2$
Gyroscope	22.378×10^{-6}	$(rad/s)^2$
Magnetometer [1]	7.841×10^{-6}	-

[1] normalized

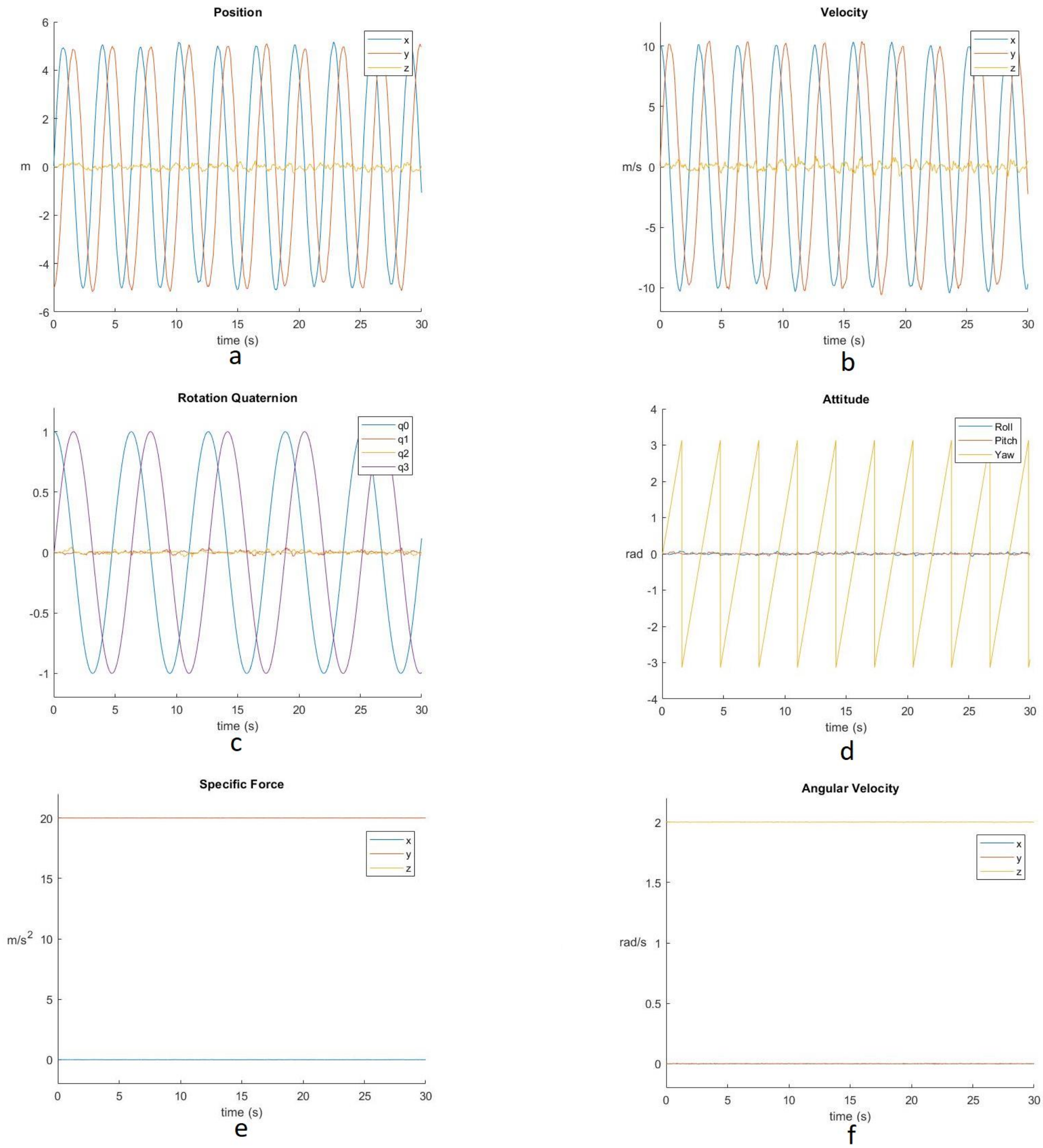

Figure 7. Simulation results of multi-sensor data fusion for uniform circular motion: (a) position; (b) velocity; (c) rotation quaternion; (d) attitude; (e) specific force; (f) angular velocity.

Table 7. Standard deviation.

	Uniformly accelerated rectilinear motion	Uniform circular motion	Units
Position	22.04×10^{-3}	24.22×10^{-3}	m
Velocity	4.83×10^{-3}	4.81×10^{-3}	m/s
Rotation quaternion	46.18×10^{-6}	216.66×10^{-3}	-
Specific force	7.87×10^{-6}	8.95×10^{-6}	m/s^2
Angular velocity	11.38×10^{-6}	49.21×10^{-6}	Rad/s

To perform the second experiment, a trajectory was established on the main avenue of the Campus, starting from point *A* (latitude -22.0024, longitude -47.9303) and passing through the points *B*, C, *B* and *C*, and finally ending at the origin. The position of the control points is shown in Fig. 8a. This path was carried out on foot, carrying the laptop in a backpack and holding the box with the setup in the hands, as shown in Fig. 8b. The results obtained are shown in Fig. 9. As can be seen in position graphs of Fig. 9b, the displacement estimated by proposed sensor fusion is consistent with the path. In addition, the altitude shown in position versus time graph, Fig. 9a, remained relatively constant, as expected. In the velocity and specific force estimation, Fig. 9c and Fig. 9f, are found periodic peaks that can be attributed the perturbations due walking motion. In Rotation Quaternion and Attitude graphs, Fig. 9d and Fig. 9e, can be observed the orientation changes which were performed in control points *B* and *C*, showing a consistent orientation result. Due to unavailability of a reference for path, it was not possible to carry out a quantitative analysis in the final experiment.

Figure 8. Second experiment: (a) control point positions; (b) transport of setup during the experiment.

4. CONCLUSIONS

This work presented a single-stage sensor fusion model that fuses data from gyroscope, accelerometer, magnetometer and GPS to estimate the position and orientation of the frame minimizing the drift. The inclusion of the biases for the acceleration and angular velocity sensors in the navigation equations allowed to minimize the constant bias errors. In addition, a preprocessing step has been proposed to remove the frequencies considered as noise by means of a digital FIR filter. The experiment results showed that the proposed algorithm was able to provide a robust and stable estimation for the position and orientation. Furthermore, the standard deviation obtained in the simulation demonstrated that the system was able to minimize the effect of sensor noise.

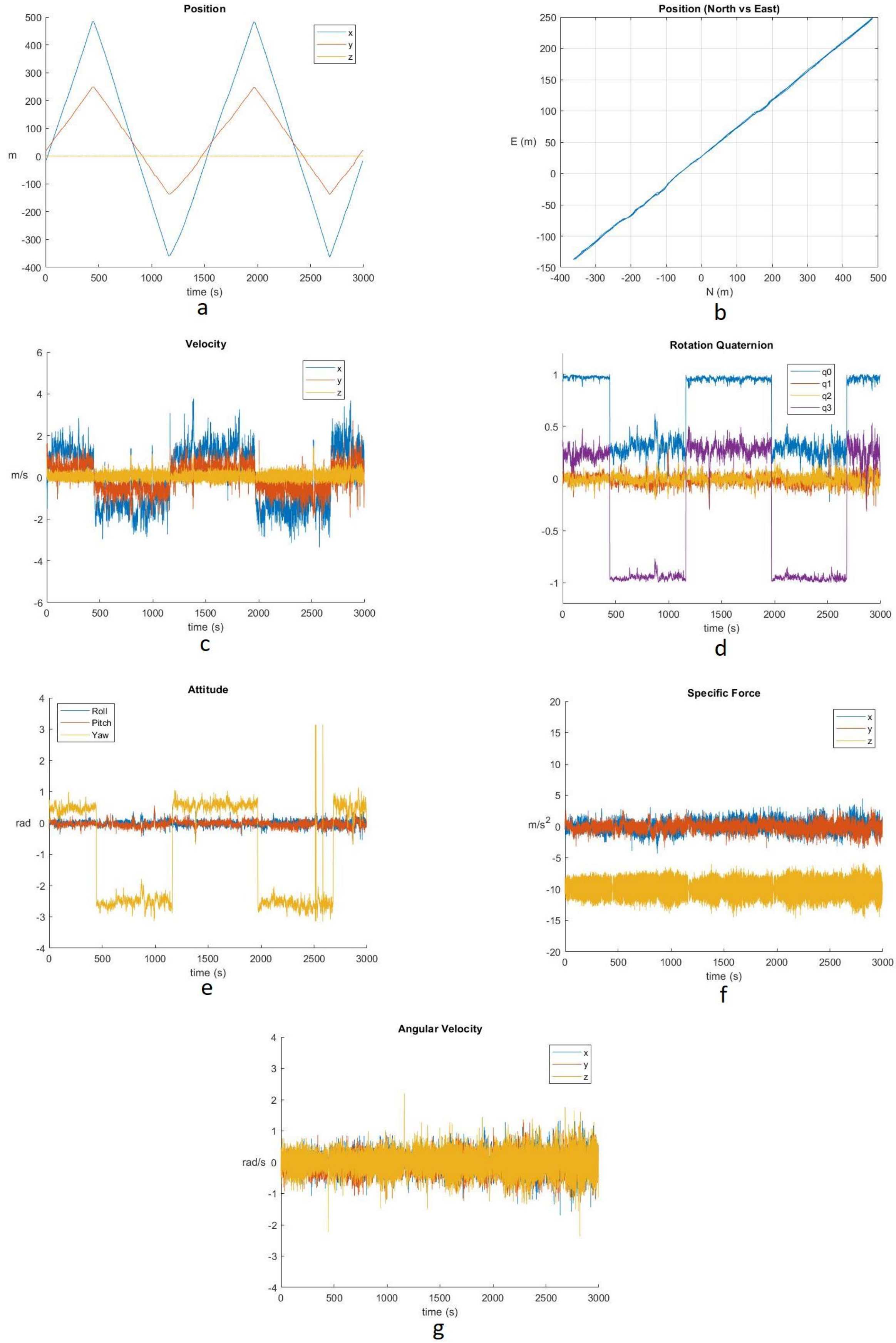

Figure 9. Estimates of states by the multi-sensor data fusion: (a) position; (b) position (North vs East); (c) velocity; (d) rotation quaternion; (e) attitude; (f) specific force; (g) angular velocity.

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