Characterization of error sources in an inertial unit using Allan variance and nonlinear parameter adjustment

W A Hernandez¹, J S Castillo-Corredor¹, J A Ramos-Cifuentes¹, F Fuentes², and L F Castañeda¹
¹ Facultad de Ingeniería Mecánica, Electrónica y Biomédica, Universidad Antonio Nariño, Villavicencio, Colombia
² Centro de Investigación en Ciencias Básicas y Aplicadas, Universidad Antonio Nariño, Bogotá, Colombia
E-mail: wahernandezb@uan.edu.co

Abstract. Locating in space is essential for devices that perform navigation. Currently, inertial measurement units have been developed to allow navigation, however, this type of sensors present different errors in measurements. They have different errors that appear and accumulate when measurements advance. For this reason, the characterization of the error sources presented in sensor BNO055 is performed; data is acquired using a Raspberry Pi and Allan’s variance method was used for data analysis. A parameter fit is made in the error equation using the Levenberg-Marquardt numerical method a method commonly used in experimental physics.

1. Introduction
The use of Inertial Measurement Units (IMUs) is wide in applications that require device orientation [1] as ergonomic studies [2], drone navigation [3] or camera stabilization [4] among others. An inertial measurement units (IMU) is an electronic device designed to measure autonomously the changes that occur in the angular speed, the linear acceleration and in some cases the magnetic field, from one or more orthogonal axes [5].

Due to the construction the IMUs have several intrinsic errors error sources which represent different aspects of the sensor. To characterize those errors is a common among other techniques the Allan variance [6]. This technique initially developed to characterize atomic clock errors becomes the standard method for IMUs error characterization by Institute of Electrical and Electronics Engineers (IEEE) [7]. From the Allan variance a data set is obtained, this data has to be fitted to a series of slopes where each one is related to some special error source. To fit those slopes an automated process has been developed [8].

In this work we present the results of the error characterization of the IMU BNO055 collecting measurements with the low cost Raspberry Pi and using the Allan variance method and applying the automated method of Jurado. In the section 2 the experimental methodology is presented using the Raspberry Pi, then in section 3 the Allan variance procedure is shown and the algorithm used is explained. In section 4 are presented the results obtained using the automated parameters fit method. Finally in section 5 the conclusions are presented.
2. Experimental methodology

Sensor recognition was performed by constantly bibliography and user manuals consulting, for the inertial sensor BNO055 and the Raspberry Pi.

The IMU that was used in this work was the Adafruit BNO055 board, which has 9 degrees of freedom and allows to read the data thrown by I2C ports (inter integrated circuits) or via universal asynchronous receiver-transmitter (UART), this board has dimensions of 20 mm wide, 27 mm long and 4 mm thick, it also has a 3.3 V voltage regulator for operation. The connection of the BNO055 sensor is made through the serial UART mode following the specifications found on the Adafruit page, since this sensor can present problems when used through its I2C interface, which causes conflicts between the internal clock of the IMU and that of the Raspberry Pi generating a delay in the communication. Before making the connection between the two devices, it is important disable the use of the Raspberry Pi serial kernel. The pin connection diagram between the Raspberry general-purpose input/output (GPIO) port pins and the Adafruit BNO055 is shown in Figure 1 and the pin names are shown in Table 1. The pin names of the Raspberry and Adafruit BNO055 are the standard given by the manufacturer in the user manuals. After having checked the communication between the Raspberry Pi board and the IMU sensor, we proceeded to make the connection between the raspberry and the computer through the virtual network computing (VNC) protocol. The data collection was performed during 6 consecutive hours and at a fixed angle of 20 degrees in z axes. To capture the data, the Adafruit package was installed and changes were made in order to visualize the data and store it in a file. At the end of the data collection process 21,600 points were collected with a sampling rate of 1 samples/second.

![Figure 1. Pin connections of the Raspberry with the Adafruit BNO055.](image)

| Raspberry | Adafruit BNO055 |
|-----------|----------------|
| 3V3       | VIN            |
| GND       | GND            |
| 15 RXD    | SDA            |
| 14 TXD    | SCL            |
| PWR       | PS1            |
| 18        | RST            |
3. Allan variance
The variance of Allan named after David Allan was initially developed for the analysis of the sources of error found in atomic clocks [6], over time it was found that it could be used to identify sources of error in accelerometers and gyroscopes using the slope method to analyze measurements from Allan variance. In general, the Allan variance $\sigma_a^2$ of a continuous time signal $\Omega(t)$ is given by Equation (1), where the signal $\Omega$ is sliced in intervals of length $\tau$, called the average time.

$$\sigma_a^2(\tau) = \frac{1}{2(N-2n)} \sum_{k=1}^{N-2n} [\Omega_{k+1}(\tau) - \Omega_k(\tau)]^2.$$  

(1)

In Equation (1), $N$ is the total number of measurements, $n$ is given by $n = \tau/\Delta \tau$ and $\Delta \tau$ the signal sample rate. Once the Allan variance is calculated, in our case using the library “allantools”, it is fit the function given by Equation (2).

$$\sigma_a^2 = \left(\sigma_q \sqrt{3\tau^{-1}}\right)^2 + \left(\sigma_{rw} \tau^{-1/2}\right)^2 + \left(\sigma_b \sqrt{\frac{2 \log(2)}{\pi}}\right)^2 + \left(\sigma_{rrw} \frac{1}{\sqrt{3}} \tau^{1/2}\right)^2 + \left(\sigma_{rr} \frac{1}{\sqrt{2}} \tau\right)^2,$$  

(2)

where each term correspond to one kind of error. The $\sigma_q$ term corresponds to the quantization error caused by the analog to digital conversion. $\sigma_{rw}$ is related to the random walk process. The bias instability error $\sigma_b$ is related to the drift of the measurement as time goes by. The $\sigma_{rrw}$ term is related to the random walk process in the rate of the measured signal. Finally $\sigma_a$ is due to the deterministic deviation of the signal measurement rate. Therefore, the above mentioned terms characterize the different error sources for the IMU sensor, then it is necessary to find the value of each one [8].

4. Error parameters calculation
To find the different error parameters it is necessary to fit the Allan variance to Equation (2). The problem is that this equation is nonlinear in the $\sigma_{xx}$ parameters, then a nonlinear parameter method is needed. In this work it was used the non linear least-square method of Levenberg-Marquardt. This method is an enhancement of the Gauss method, based in a search of the minimum by using a linear approximation [9, 10]. This method is commonly used in plasma physics in data analysis of Langmuir probes measurements of temperature, density and potential [11,12].

The fit of the parameters is performed in “python” using the function “least_squares” from the “scipy” library. An important point of the method is the needed of an initial guess for the parameter to initiate the fit process. To bring an initial guess, following the process proposed by Jurado et al. [8], the linear approximation given by the Equation (3) is fitted.

$$\sigma_a = \sqrt{3\tau^{-1}} \sigma_{q0} + \tau^{-1/2} \sigma_{rwo} + \sigma_{b0} + \frac{1}{\sqrt{3}} \tau^{1/2} \sigma_{rrw0} + \frac{1}{\sqrt{2}} \tau \sigma_{rr0},$$  

(3)

where the zero sub-index indicates a linear approximation of the parameters given in Equation (2). Once the parameters are obtained they are used as a guess for the Levenberg-Marquardt using the Equation (2). The results of the linear approximation and the complete nonlinear model are show in Figure 2. It can be seen that the linear model oscillates around the experimental data, but it can be used as a tool to guess the initial values for the complete non-linear equation.

The numerical values of the error parameters in Table 2; these values have to be taken with care as the fit is not good enough in the increasing side of the curve, which as shown in [8] them corresponds to the $\sigma_{rrw}$ and $\sigma_{rr}$ parameters.
5. Conclusions
In this work was presented a cheap process to characterize the error sources for an IMU sensor for research purposes. Also the process has a pedagogical use in experimental physics and engineering to exemplify the electronic and data analysis techniques for sensors characterization. Also it was shown that python is useful as a tool for pedagogical purposes in experimental data analysis, due to the powerful libraries, high quality and easy to use graphics library and as free software tool. It is proposed as a future work use the error characterization as a first step to implement “in situ” calibration techniques to apply this IMU to control develop a drone position control.

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