

## **MEMS Technology Evaluation for Submerged Vehicle Navigation**

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*The article undertakes analysis of some vital aspects of inertial navigation using MEMS. Although MEMS inertial sensors offer affordable, scaled units, and though their inherent measurement noise can be relatively easily mitigated, there are still parameters due to which they are not currently capable of meeting all requirements for accurate inertial navigation. The article presents a few aspects of MEMS gyro errors, and their estimation process in the context of INS processing flow. These errors have a serious impact on overall inertial system performance. The results of undertaken researches in that area, and pointing out the main difficulties behind the INS when using a few top MEMS technologies, were presented as well. The paper clearly states, that current MEMS technologies, including sophisticated software, does not fulfil submerged inertial navigation whilst operating in dynamic conditions, due to linear acceleration, affecting gyro performance.*

**Keywords:** MEMS, IMU, INS

### **1. Introduction**

An inertial navigation system possesses a relatively straightforward idea behind it, based mainly on gyroscopes and accelerometer sensors [2]. Gyroscopes are critical rotation sensing elements used in inertial measurement units (IMUs) for attitudes measurement in heading and reference systems (AHRS); and in the wider perspective, in inertial navigation systems (INS). For INS processing flow, the gyroscopes are used through DCM (direction cosine matrix) or quaternions [6]. There are many IMU application areas besides inertial positioning, e.g.: spacecraft, marine vehicles, manned and unmanned aircraft, and surface vehicles. It can be mentioned, that gyroscopes are very important elements in vertical accurate stabilization systems, as well. The gyro technologies include: still being improved, ring laser gyros (RLG), relatively expensive fiber-optic gyros (FOGS), low cost micro-electro-mechanical (MEMS) gyros, and obviously, spinning mass mechanical gyros.

Ring laser gyro (RLG) is currently the industry standard for precision rotation measurement. The principle of operation of a RLG is: two counter-propagating laser beams have different

frequencies, with the difference dependent on rotation rate. The difference provides the rotation angle or rotation rate around the RLG's sensitive axis. RLG has demonstrated capability of measuring an arc-second rotation.

On the other hand, low-cost MEMS inertial sensors emerged over the past decades and MEMS researchers have demonstrated a number of microsensors for almost every possible sensing modality, including attitudes. Current MEMS inertial measurement units (IMUs) come in many shapes, sizes, and costs, depending on the application, and performance required. MEMS sensors have proved and demonstrated performances exceeding those of their macroscale counterpart sensors [9]. Obviously, the MEMS sensor quality is crucial for further records processing from IMU systems, especially in the context of attitudes in INS. A few of the top MEMS technologies, as presented in Fig. 1, will be analyzed in the article, especially the dynamic aspects of MEMS gyro bias. In this context “dynamic” means close to or overcoming 0.5g.

## 2. MEMS Gyro Current Capabilities

Interesting results were obtained from [16], where the different IMUs based on MEMS technology, were presented in a very demanding context, where 10cm resolution at 100m is required [16]. For the experiment an accurate motion reference unit (Seatex MRU Calibration Certificate) from Kongsberg was chosen, and a few other top IMU units were compared. The paper proved, that current MEMS technologies satisfy as to rotation stability.

However, in the context of inertial positioning and linear acceleration, an angular error of 0.1 degree for 10 meters/s<sup>2</sup> (that equals G gravity acceleration), results in a near 2 cm/s<sup>2</sup> linear horizontal acceleration error, and for a 1 degree linear horizontal error gives circ. 17 cm/s<sup>2</sup> (Fig.2). Both are not currently acceptable in INS applications, because e.g. only 2 cm/s<sup>2</sup> linear acceleration error gives 1 m error after 10s.

The most important part of IMU are the accelerometer and gyroscope sensors. INS utilize them, adding navigational algorithms, but it is well-known what a challenge it is [7], [8]. IMU performance is typically driven by the gyroscope bias. A standard statistical characterization of the bias performance is bias instability, which indicates the magnitude of random variation that can be expected from a signal over time. In the gyro the random variation is in units of degrees per hour. But even in the narrowed AHRS (*Attitude and heading reference system*) application context, these sensor errors are still a serious issue.

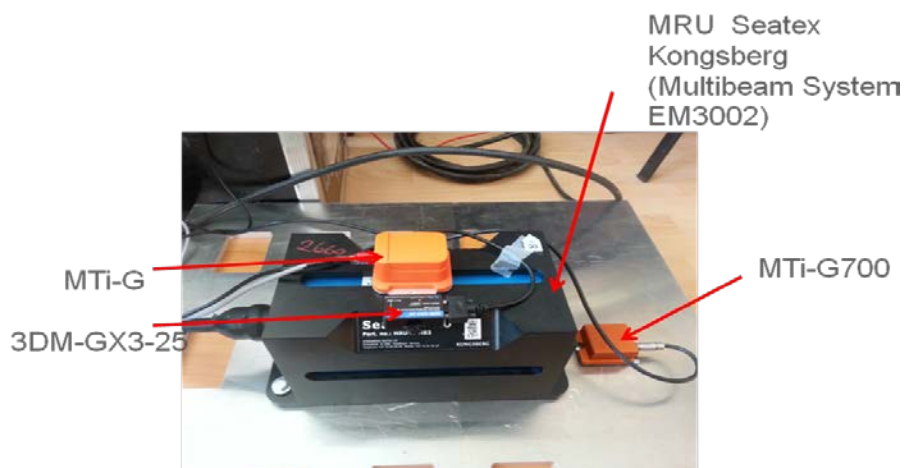


Fig. 1. Rotation quality comparison test using a few MEMS based IMU devices

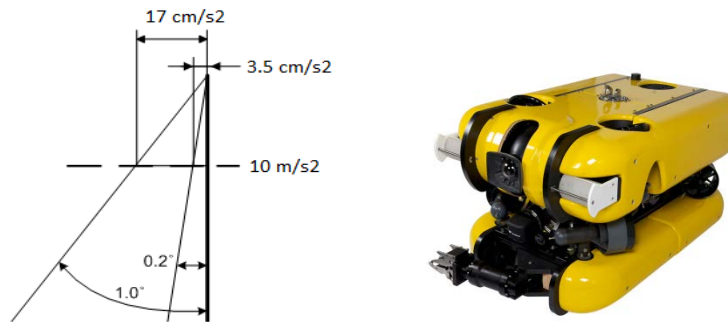


Fig. 2. Impact of the rotation error on the IMU in dynamic condition

To fulfill the requirements, usually a Kalman estimator reads in the sensor data from the accelerometer, and angular rate from the gyro, which are the part of the system state vector, and in turn output, the Euler angles (or quaternions), so attitudes and bias of the gyros are calculated [16]. The Kalman filter uses knowledge of the deterministic and statistical properties of the system parameters, and the measurements, to obtain estimates which are optimal (Fig.3). It is an example of a Bayesian estimation technique; and is supplied with initial estimates, usually a one dimensional matrix, and then operates recursively updating its working estimates with an optimal weighted average of their previous values, and new values derived from innovation measurement. The Kalman filter is kind of fusing sensor algorithm as well, which fuses in the case of IMU: the gyroscope sensor angular rate (AR), burden with the AR bias and the acceleration sensor, not burden with a bias to some extension.

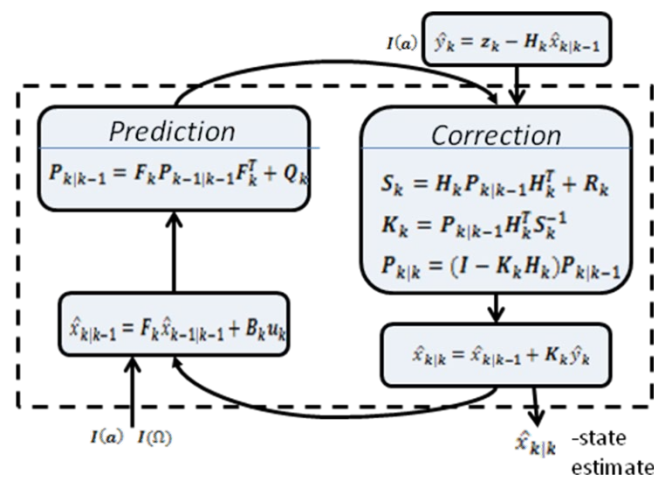


Fig. 3. Kalman filtering algorithm

In Fig. 3,  $\hat{x}_k$  stands for matrix state estimation, which consists of linear acceleration from accelerometers  $I(a)$ , angular velocities from gyroscopes  $I(\Omega)$  and attitudes,  $\mathbf{P}_k$  stands for process covariance,  $y_k$  – innovation,  $z_k$  – current measurement,  $K_k$  – Kalman gain,  $\mathbf{H}_k$  – measurement matrix,  $\mathbf{R}_k$  – measurement error variance,  $\mathbf{Q}_k$  – model variance and  $\mathbf{F}_k$  stands for process model.  $\mathbf{B}_k$  may be interpreted as a control matrix.

IMU gyros are typically of higher quality, but burden with a bias as integrated over time resulting in a drift. The drift over time results in unreliable input for further processing in an INS system, and some compensation is required. So another sensor is required to provide a second tilt or orientation measurement to remove drift and improve the real orientation of the system (Fig.2). An accelerometer or magnetic sensor is a typical choice. However, the

magnetic sensor is subject to the influence of the physical environment, and cannot measure a pitch, but only roll and yaw and is not always reliable again, so the accelerometer sensor is the only choice in practice.

### 3. Gyro AR integration in static conditions

Following that, operational measurements for a few IMU devices, as presented in Fig. 1, were carried out simultaneously. MRU (see Fig.1) from Kongsberg is specially designed for high precision motion measurements in marine applications, and for users requiring high accuracy roll, pitch, and heave measurements. After that the straightforward gyro bias compensated AR integration for all IMU devices was carried out, with an additional smartphone gyro for comparison as presented in Fig.4a.

Fig.4b presents results of AR integration for these IMU technologies, after a bias removal. This figure proves MEMS gyro quality. The right part of the Fig.4b, shows real pitch after Kalman fusion algorithm calculation. That part of the Fig. 4b presents how the real pitch is moved about -1deg, but that part of the figure representing four devices AR integration resulting in rotation starts from zero rotation, because initial rotation can't be observed by the AR gyro sensor.

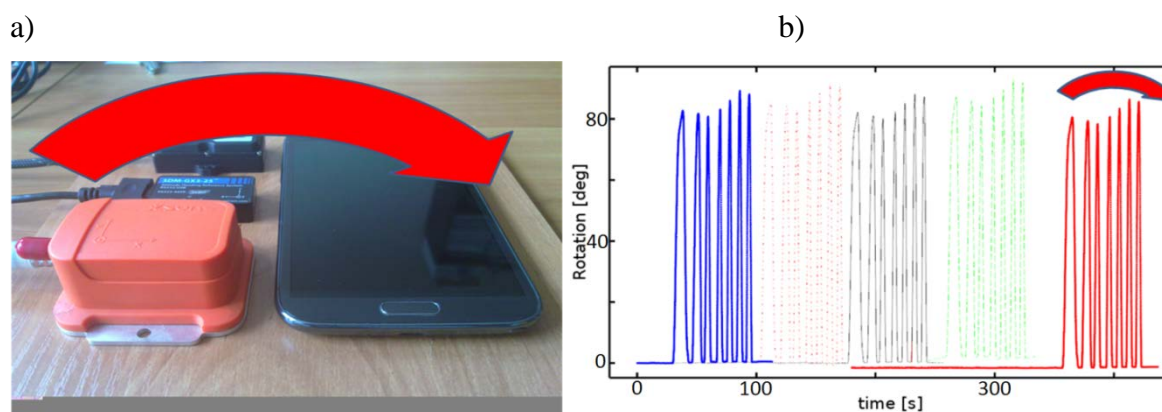


Fig. 4. a) Angular rotation. b) Rotation as a result of AR integration for four IMU technologies, counting from left, fourth (green) is for smartphone b).

The gyros AR integration as presented in Fig.4a, proves their high quality, because obtained results are comparable to the mentioned Kongsberg MRU tested device (see Fig.1) and for instance for MRU the standard deviation equals 0.022579, for MTi-G700 0.076428, 3DM-GX3-25 0.034849 and for MTi-G equals 0.15256. Standard deviation and variance error were obtained from operational tests as presented in Fig.1, 4.

### 4. Gyro Two Sample Variance Evaluation

Two Sample Variance Evaluation is a method of analyzing a sequence of data in the time domain, to measure frequency stability in oscillators. The variance, also known as Allan variance is named after David W. Allan [10]. The method can also be used to determine the noise in a system as a function of the averaging time, and is a popular method currently for identifying and quantifying the different noise terms in inertial sensor data. The results from this method are related to five basic noise terms appropriate for inertial sensor data. These are quantization noise, very important angle random walk, bias instability, and rate random walk.

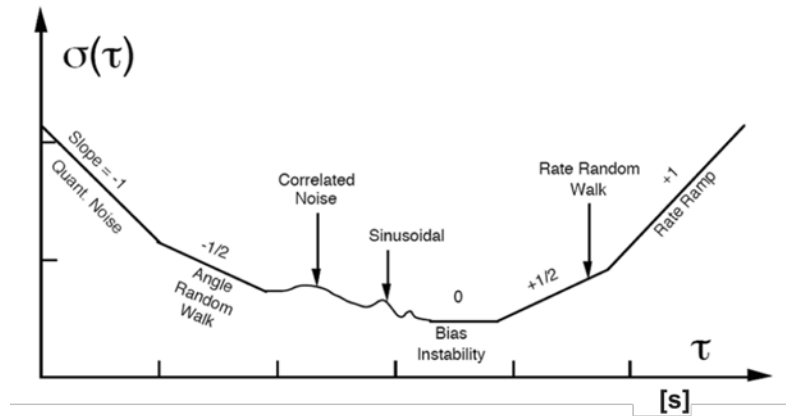


Fig. 5. Gyro Allan variance

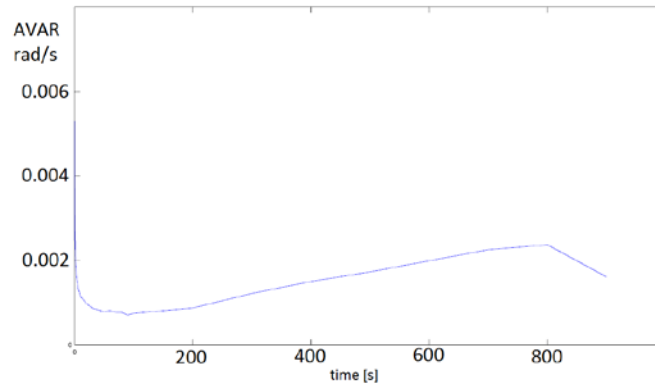


Fig. 6. Allan variance for 3DM Gyro example in linear scale

Tab. I presents some typical bias errors which possess the most important impact on the IMU final tilt observations. These are important parameters in the context of the underwater system attitudes evaluation. All these MEMS gyro errors can be evaluated from Allan variance, see Fig.5. The in-run bias stability typically references the minima of the Allan variance curve (Fig.5). That is also known as an in-run bias, in the static conditions and with ideal integration

TABLE I. MAIN GYRO ERRORS

Gyroscope Dynamic Accuracy	MRU (EM3002)	3DM-GX3-25	MTi-G700	Smartphone
Angle Random Walk [deg/h <sup>-1/2</sup> ]	0.7	2.3	2	3.5
Bias [deg/s]	0.1	0.25	0.2	1
In-run Bias Stability [deg/h]	8	44	10	20
Non-linearity [% FS]	0.2	0.1	0.01	0.1

## Conclusions

High quality sensors are a matter of fundamental importance in the inertial navigation context, that is almost obvious. Though low cost MEMS gyros are still proving their high quality, but are not perfect (as all sensors) and introduce small errors in each measurement. The paper draws attention to the dynamic aspect of MEMS gyro bias. Accelerometer sensors currently present quite good quality for short range INS processing, gyros are still behind in some of the presented technologies, but progress in the area is still observed. The last question is if these technologies can be used in INS; in the authors opinion they can be, but in non-shocking, close to stable, conditions. Finally the paper clearly states, that current MEMS technologies, including sophisticated software, does not fulfill the parameters for underwater inertial navigation as operating in dynamic conditions, due to linear acceleration (Fig. 3).

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