

Quantum-Based Relative Inertial Navigation with Velocity-Aided Alignment and Initialization [†]

Pieter Simke de Vries ^{1,*} , Jim Rojer ² and Floris E. Kalff ³ 

- ¹ Intelligent Autonomous Systems (IAS), Netherlands Organization for Applied Scientific Research (TNO), Oude Waalsdorperweg 63, 2597 AK The Hague, The Netherlands
- ² Heat Transfer and Fluid Dynamics (HTFD), Netherlands Organization for Applied Scientific Research (TNO), Oude Waalsdorperweg 63, 2597 AK The Hague, The Netherlands
- ³ Electronic Defence (ED), Netherlands Organization for Applied Scientific Research (TNO), Oude Waalsdorperweg 63, 2597 AK The Hague, The Netherlands
- * Correspondence: pieter.devries@tno.nl
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Abstract: Quantum sensors are expected to offer significant advantages in magnetic- and gravity-aided navigation. However, these techniques depend on the local environmental conditions and require an alternative solution to ensure high position accuracy on shorter timescales. This paper explores the potential of a hypothetical quantum Inertial Measurement Unit (IMU) with much better performance than classical IMUs when used for dead reckoning position estimation preceded by an alignment period to achieve a relative inertial navigation solution. We show that significantly reduced noise levels (velocity random walk) for the accelerometer and/or gyroscope cannot be automatically exploited. In practice, axis misalignment and initial state errors in orientation limit performance. Incorrect orientation causes errors in compensating for the gravity vector, having a dominant effect. This research proposes to introduce an alignment period with a reliable velocity sensor, prior to starting the mission relying solely on inertial navigation. The orientation errors can be estimated with numerical optimization, in which we match the dead reckoning estimate to the reference velocity signal. The fact that quantum IMUs have a much more accurate measurement means that these orientation errors could be compensated much more accurately. When mitigating these dominant error sources, there is a significant benefit to using a quantum IMU for inertial navigation. The initial position error growth is significantly smaller than existing systems. Some estimates are given for the necessary quality of the IMUs to benefit from these protocols and offer a similar position solution quality to high-end or military-grade IMUs. In the future, military operations that do not rely on Global Navigation Satellite System (GNSS) for their Positioning, Navigation and Timing (PNT) information may be performed with unprecedented position accuracy when using a quantum IMU complemented with velocity-aided alignment period, thereby increasing the effectiveness and dependability of the operation.

Keywords: inertial navigation; quantum sensors; sensor fusion



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1. Introduction

The main aim of this research is to find ‘calibration’ methods and facilitate sensor (suite) design to optimize short-term (<4 h) GNSS-denied operational capability in military scenarios by improving the position drift performance of TNO’s Navigation Solution Estimator (NSE): the Timing, Orientation and Positioning Service (TOPS) Fusion Engine. This is in contrast to other proposed contemporary GNSS-denied navigation methods such as the magnetic-aided inertial navigation system (MAINS) and the gravity-aided inertial navigation system (GAINS), which guarantee inertial navigation system (INS) accuracy over longer time-spans, but may not be suited for all operational scenarios since accurate magnetic or gravity anomaly maps of the operational areas are not available

(making high-resolution maps requires low-altitude surveying with advanced (military or otherwise technologically sensitive) equipment, which is often not possible in contested or non-friendly territory).

The potential of an INS with quantum-based IMU is shown as a means of GNSS-denied navigation for short (<4 h) mission durations. First, a significantly reduced sensor measurement noise was investigated, and major error sources identified. In a second phase, the effects of these major error sources was mitigated by the use of a dynamic alignment and initialization (DAI) procedure. This procedure uses a velocity sensor such as a Doppler velocity log (DVL) for alignment in a suitable environment before relying solely on pure inertial navigation. With this DAI procedure, the position drift can be significantly (10–100×) reduced, and military operational capability in hostile environments can be extended.

1.1. Inertial Navigation Basics

The unavailability, being denied or even spoofed, of the GNSS poses a significant threat to military operational capability. In the 1940s, a steady development in inertial navigation using (electronic) sensors began. Since then, mathematical algorithms, in computer systems, have been used to translate the measurements of the inertial instrumentation to orientation (pitch, roll and yaw), as well as position and velocities in the three axes. Today, readily available strong computers with excellent size, weight and power (SwaP) characteristics allow for high-quality positioning and orientation solutions.

1.2. Advanced Inertial Navigation

More advanced and expensive INSs offer better physical sensing elements. Their principles, being fiber-optic gyroscope (FOG)-based or ring laser gyroscope (RLG)-based, offer superior sensing performance with respect to less expensive microelectricalmechanical system (MEMS) IMUs. Typically, also more advanced processing algorithms are used in these INSs, as well as better processing hardware. This results in a better navigation performance of these INSs.

1.3. Major Error Sources

Inertial navigation is sensitive to disturbances such as sensor bias (and stability/flicker noise) as well as measurement noise (thermo-mechanical white noise, or angle random walk) [1]. While more expensive sensors typically perform better on these characteristics, most of their advantages would be negligible if major error sources are not considered:

1. The misalignment between IMU measurement axes; since these sensors are not manufactured perfectly, the axes have an unknown residual misalignment.
2. The initial orientation of the vehicle with attached INS, when starting the inertial navigation.

State-of-the-art sensor characteristics would result in a position drift in the order of 1100 m per hour [2]. As will be discussed in Section 2.1, the significance of the effect of these error sources resulted in the development of the DAI routine, introduced in Section 1.5 and further explained in Section 2.4.

1.4. Quantum Potential

Over the past decade, quantum sensing principles have been explored, mostly in a laboratory environment. These offer great potential for inertial navigation due to their characteristics [3]. Sensors utilizing a nitrogen-vacancy center (NV center) offer very low measurement noise while cold atom interferometers (CAIs) offer a bias-free, although somewhat noisy and irregular, measurement frequency-wise [4].

1.5. Mitigation of the Effects of the Error Sources

The above sections consider the limitations of inertial navigation subject to the major error sources. This chapter will concern the mitigation of the effects of these error sources.

A DAI procedure is proposed, in which a velocity sensor will be used to estimate the initial orientation error. The velocities of the vehicle are estimated in its INS. The initial velocity (typically zero), initial orientation as well as measured accelerations and angular velocities are used to achieve this. In the DAI routine, the initial orientation angle is optimized such that the weighted mean square error of the velocity measured by the DVL and estimated by the INS are minimized. After the routine, inertial navigation (even without the availability of the velocity sensor) can be used to obtain far greater accuracy, thereby scaling with the improvement in sensor characteristics such as measurement noise. A quantum-based sensor, having a measurement noise 10–100 times lower than the current state-of-the-art, may be able to navigate with a drift performance that improves by a factor 10–100, reducing the drift to 110–11 m/h, respectively. More advanced contemporary INSs, such as those possessing high-end IMUs based on a RLG, may also benefit from a DAI. However, these INSs also use other, proprietary methods to improve dead reckoning position estimation accuracy over longer periods of time. It is beyond the scope of current and near-future research to reverse-engineer these methods. Lower-end INSs are limited by their sensor performance, as discussed further on in Section 3.2.

2. Materials and Methods

This section details the methods used in this research. The materials used are solely software programs written in Python and C++, contained in TNO's PNT software suite: TOPS. Especially within the the TOPS research tool, the simulation enhanced sensor designer (SENSED) is extensively used and improved through the course of this research.

2.1. Phase 1: Identification of Major Error Sources

The major error sources of using dead reckoning inertial navigation are identified through simulating three different scenarios:

1. Using a FOG IMU and two potential hypothetical quantum IMUs during a 10 s flight, evaluated using the Euclidian position error at the final time.
2. Using a FOG IMU and two potential quantum IMUs during a 10 s flight, evaluated by the Euclidian position error at the final time. IMU axis non-orthogonalities (in pitch, yaw and roll), generated from a normal distribution with zero mean and 0.1 degree standard deviation, are considered.
3. Using a FOG IMU and two potential quantum IMUs during a 10 s flight. The evaluation criterion is the Euclidian position error at the final time. Multiple combinations of initial orientation errors (in pitch, yaw and roll) are considered:
 - (a) A range of initial orientation errors in only yaw;
 - (b) A range of combination of initial orientation errors in both pitch and roll;
 - (c) A range of combination of initial orientation errors in pitch, roll and yaw.

An evaluation period of 10 s is chosen. Since the effects in this elementary analysis are linear, they can easily be extrapolated. Longer periods do not provide extra insights.

2.2. State Estimation with TOPS Fusion Engine

At the center of TNO's PNT software suite is the fusion engine. It allows multiple types of interfaces with other (online) system modules and middleware, such as Robot Operating System (ROS) [5] or other common communication protocols. It incorporates a multitude of vehicle and sensor models. At the core, an unscented Kalman filter (UKF) [6] is used to use vehicle models and sensor measurements (either synthetic or real world) to perform sensor fusion and state estimation.

The TOPS Fusion Engine has been used in various projects at TNO and has recently been applied in a successful field test using a BlueROV unmanned underwater vehicle [7]. Showing minimal deviation from the reference real-time kinematic (RTK) positioning Global Positioning System (GPS), it allows for autonomous underwater navigation [8]. Previously existing systems were an order of magnitude larger in terms of SwaP than this vehicle, required a far larger vessel and significantly more crew to deploy and are around

twenty times more expensive in capital expense. This all results from the TOPS Fusion Engine's capability to leverage the sensor qualities to a far greater extent than existing PNT systems do.

2.3. SENSED Software Tool and Workflow

Within this research, another part of the TOPS software suite, SENSED, was used. A significant amount of time was spent to make the code base understandable and re-useable for future research. That is, the code was explicitly designed such that it can be connected to different simulation platforms, fusion engines and can utilize different sensor models. This allows the code to be used for new use-cases with different vehicles and different sensor suites.

The workflow in SENSED was designed as a robust and general method. The method is repeatable and easily adjusted to incorporate other sensors, other waypoints or even another vehicle. By configuring a plant model (=vehicle) and selecting which sensors are used, a workflow is easily configurable.

In essence, SENSED is a procedural fusion engine configuration manipulator. A researcher can formulate a 'research plan' in the form of a simple Python script. In this script, they can define what sensor(s) (combination/characteristics) to evaluate or optimize. Its genesis was driven by the realization that the utility of improving sensor characteristics in (more) expensive sensors (such as IMUs, but also magnetometers, barometers, among others) in a sensor fusion framework, such as a Kalman filter, can only be evaluated by simulating the sensors (or using measurement data) and then passing it through the Kalman filter-based fusion engine. The pragmatic goal was to find the least expensive sensors that would still achieve the position drift performance required by the customer. At the core of SENSED is a sensor simulator which generates sensor time-histories based on sensor specification sheets. Using a multitude of realizations (=parameters such generated from a stochastic distribution described by the sensor specifications), the performance of a set of sensors and their characteristics in a certain operational scenario may be evaluated and optimized using the TOPS Fusion Engine.

2.4. Phase 2: Alignment and Initialization

Most current INS systems utilize a stand-alone alignment and initialization period in which they require a period of ≈ 5 min under standstill conditions. During this phase, the gravitation vector measured by the accelerometers is utilized to establish a local vertical and establish roll and pitch angles. In the same period, the north-finding algorithm tries to detect the Earth's rotation in the gyroscope's measurement to establish a heading estimate. In practice, the vehicle cannot be fully at a standstill and the high number of degrees of freedom with sensor-biases and angle errors cause inaccuracies in the order of 0.005° [9].

This research proposes to perform a dynamic, velocity (measurement)-aided alignment and initialization phase to specifically minimize the orientation errors of the initial state, the unknown residual within-sensor non-orthogonality and manufacturing/installation misalignments. The advantage of DAI is that the vehicle does not have to be at a standstill and no errors will be made by violating such assumptions. Furthermore, the movement of the vehicle allows the effects of the different error sources more distinguishable. Therefore, the orientation errors can be estimated with higher accuracy and precision.

The DAI procedure proposed consists of three phases as seen in Figure 1. These are:

Perform DAI track (1. in Figure 1): In this phase, a figure-8-like track is covered in which all axes are excited to make the orientation errors around each axis observable. The DAI track should be executed such that the velocity measurement can be taken reliably.

Orientation estimation (2. in Figure 1): In this phase, the orientation errors are estimated by minimizing the difference between the dead reckoning velocity estimate and the measured velocity on the alignment track data through optimization.

Continue mission with dead reckoning (3. in Figure 1): In this phase, the dead reckoning is continued considering the orientation errors estimated in the previous phases.

This means that the dead reckoning should perform significantly better, and navigation solely based on the inertial measurements should be possible.

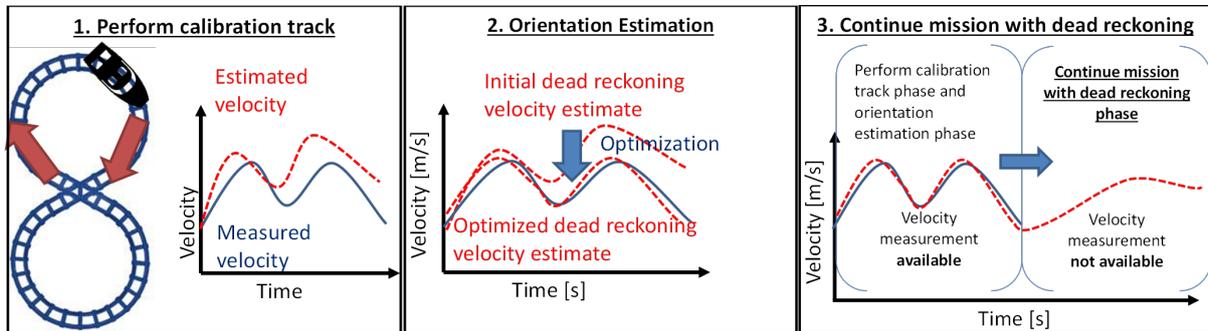


Figure 1. Dynamic alignment and initialization procedure. From left to right: 1. record measured velocity by DVL and estimated velocity by INS; 2. use optimization to find lumped non-orthogonality errors; 3. with optimized error estimate, correct for these and perform (short, <4 h) mission with adequate positioning quality.

For this research, the maritime use case was selected with a frigate or submarine in mind. This use-case was selected as these vehicles are often fitted with high-end INSs [10] and typically also have a DVL sensor fitted that can reliably measure their speed when the local seafloor is of adequate quality. However, the use of DVL in mission conditions can be limited, as its accuracy can be affected by gradients in the sea floor, and its acoustic signature may be undesirable.

It is envisioned that phase 1 and 2 would be executed in a friendly harbor or other benign environment, after which the mission can venture into more challenging or even hostile environments.

2.5. Optimization

This research aims to make a DAI procedure utilizing a quantum IMU and a velocity measurement to minimize orientation errors. This means that an optimization approach is needed that can estimate orientation errors given the DAI time-history track data. However, the question at hand is more complicated, as it also requires insight in in what sensor specifications are needed to successfully perform a DAI procedure, or how long this procedure needs to be.

The approach utilizes an inner and outer loop optimization strategy, cf. Figure 2.

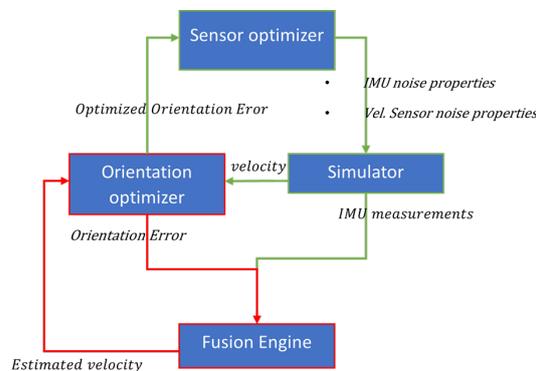


Figure 2. Optimization setup for SENSED program.

Inner Loop: Outlined in red is the inner loop optimization, the inner loop optimizes the orientation error, ϵ_θ , to minimize the dead reckoning (DR) velocity with regard to the DVL velocity measurement, as described in Equation (1). All velocities are estimated in a local reference frame. Since the length of the evaluation error due to Schuler oscillations is

minimal, their influence was briefly assessed and deemed negligible. Future research will include longer simulations and therefore revisit the influence of Schuler oscillations.

$$J = (v_{DVL} - v_{DR}(\epsilon_\theta)) \quad (1)$$

The inner loop functions on a single DAI track dataset. The fusion engine block handles the dead reckoning processing. A two-stage optimization strategy was selected. In the first stage, a Bayesian optimization method is applied. Followed by a second stage, in which a gradient descent optimization method is used. The Bayesian method was selected to avoid local minima, as the non-linear nature of orientation errors can lead to non-convex landscapes. Bayesian optimization approximates the objective function by a Gaussian process model, which can approximate any smooth function. However, many point evaluations were found to be needed to find the exact minimum. Therefore, the number of iterations of the Bayesian method was limited. Subsequently, its best solution was used as a seed for a gradient descent method, which can converge very quick to the nearby minimum. The Bayesian optimization iterations were selected to be 50, with initial test runs showing subsequent solutions all being in close to the same minimum.

Outer Loop: The outer loop is outlined in green and has two main functionalities: first, it can optimize the simulation parameters for better orientation optimization. This can both be use-case specific settings like the calibration period, as well as sensor parameters like noise power. Secondly, it can also use multiple noise realizations to avoid overfitting of the optimizer and to obtain insight into the performance spread that can be achieved in realistic conditions.

The philosophy was to implement the outer loop also as a Bayesian optimizer that would optimize the parameters of the IMU and calibration procedure. This would allow the entire calibration concept to be optimized. However, due to budget limitations, the outer loop was only implemented as a simple grid search for pre-selected parameters. This means that it is not possible to optimize the combinations of sensor properties that have interdependencies with the dead reckoning performance.

2.6. Simulation

This study aimed to analyze what parameters would induce the best orientation estimation within the inner loop. Table 1 shows the considered parameter variations for the outer loop. With the current developments in quantum measuring techniques, the accuracy (noise level) of both the accelerometer and the gyroscope are considered. Furthermore, the calibration time was expected to be of influence. The DVL accuracy could also be of influence but is expected to be less critical as there will be no cumulative errors as in the dead reckoning velocity estimate.

Table 1. Sensor reference noise values and tested ranges.

Parameter	Reference Value	Tested Range	Note
Accelerometer Noise	$\sigma = 10^{-5} \left[\frac{\text{m}}{\text{s}^2} \right]$	$[10^{-6}, 10^{-4}]$	Honeywell HG9900
Gyroscope Noise	$\sigma = 10^{-6} \left[\frac{\text{rad}}{\text{s}} \right]$	$[10^{-8}, 10^{-6}]$	Honeywell HG9900
DVL Noise	$\sigma = 10^{-3} \left[\frac{\text{m}}{\text{s}} \right]$	-	Nortek 500

Each of the three parameters is evaluated separately, meaning that when the accelerometer noise is varied, the other parameters are kept at their reference values, which are based on the current high-end sensor specifications. The reference value for calibration time was made similar to typical calibration times in inertial navigation (inertial navigation requires calibration for heading estimation). The mean value on 25 noise realizations will be used to judge the performance on each tested optimization parameter value.

3. Results

3.1. Phase 1 Results

With increasing pitch initialization error, the position error increases far more strongly than with increasing yaw initialization error, as can be seen in Figure 3. This is as expected: the pitch (and roll) angles produce an error in the perceived acceleration while the yaw only influences the (horizontal) direction.

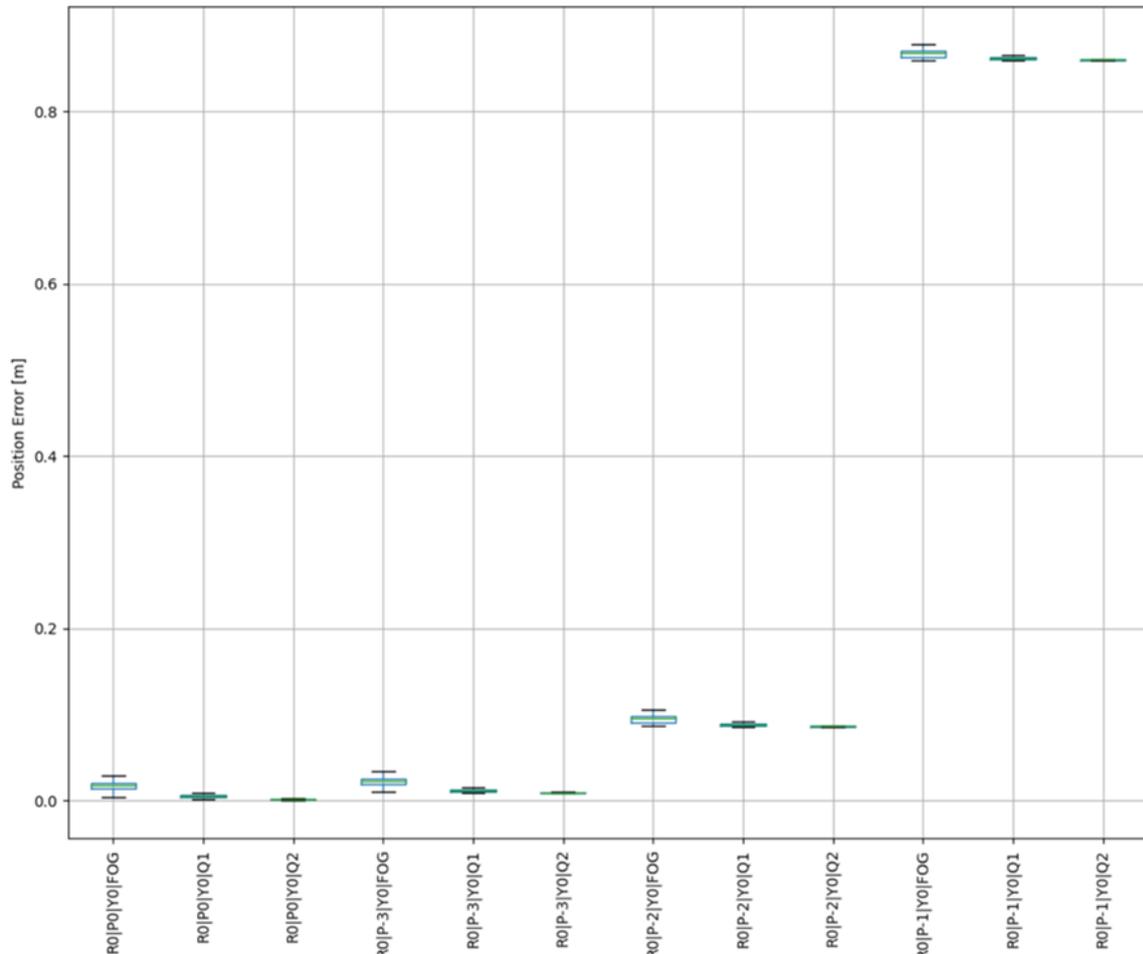


Figure 3. Phase 1 results: Increasing pitch initialization error for all IMUs, a large influence in dead reckoning performance can be seen, with the sensor noise characteristic improvements only amounting to a very small improvement in dead reckoning performance. Note the significant differences in position error between P0, P3 and P2 and P2.

From Figure 3, it can be seen that for a 10 s dead reckoning period, small initialization errors in pitch of 0.01° are already dominant over sensor noise specifications.

In real-life situations, it is possible, though difficult, to establish an initial estimate within 0.01° accuracy [11].

3.2. Phase 2 Results

The results are limited to the analysis of the gyroscope influence, since the accelerometer influence was negligible due to the one-dimensional scenario.

3.3. Gyroscope

Figure 4 shows the mean angle estimate for various gyroscope noise levels. In this case, there is clearly an improved result going for lower noise levels. The result now clearly converges to the simulated angle error of 0.045° and reaches an accuracy of about

$5 \times 10^{-5} [^\circ]$ at $\sigma^2 = 2.5 \times 10^{-15} [\text{rad/s}]^2$. This accuracy would yield an 11 m position drift in the first hour, which is improvement by a factor of 100 compared to the current state-of-the-art dead reckoning performance. The limiting factors beyond this point were not investigated due to time and budget constraints.

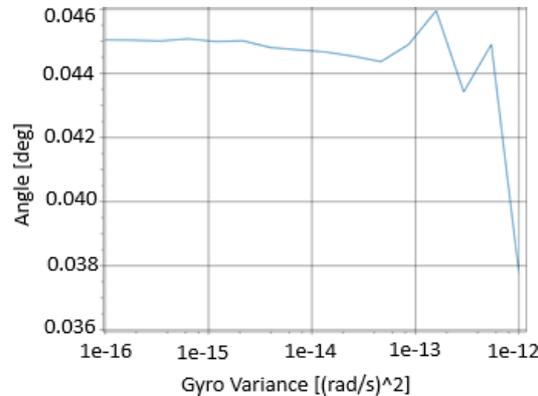


Figure 4. Varying gyroscope variance plotted against estimated pitch initialization error angle.

The noise of the gyroscope is of more importance than that of the accelerometer as the integration errors of the gyroscope lead to incorrect compensation of gravity, which is the current dominating error in dead reckoning systems.

Figure 5 shows the mean cost function (Equation (1)) and values for the different gyroscope noise levels. For values below $\sigma^2 = 10^{-13} [\text{rad/s}]^2$, the cost approaches the simulated noise level of the DVL. This is the minimum value expected out of the cost function, as lower values would indicate overfitting.

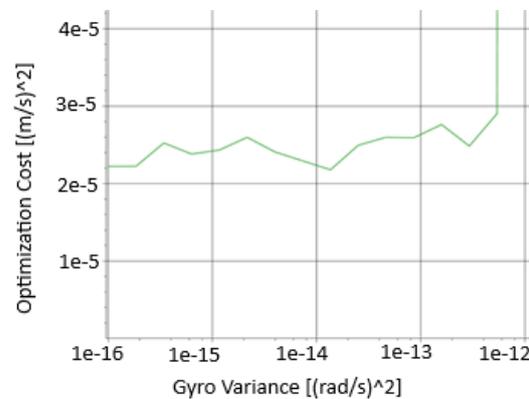


Figure 5. Varying gyroscope variance plotted against cost.

4. Discussion

In this study, only dead reckoning performance is considered. Dead reckoning is the main method in inertial navigation and is utilized by most high-end systems like the iXblue Phins [10], Boreas D90 [12], HG9900 [13] and many more.

In the first phase of this research, the major error sources were identified, and if these major error sources are not mitigated, no advantage can be observed by using better sensors. The above commercial off-the-shelf (COTS) INSs do not employ further methods to improve on this performance. The inertial navigation performance claimed by these products is in line with the simulated results presented in this study. Other systems claim better performance, incorporating other methods to improve error growth over longer periods of time, which will be investigated in future research.

In the second phase, the analysis was reduced to one dimension. The inclusion of the DAI procedure meant that the major error sources can be mitigated by the inclusion of a velocity sensor such as a DVL. The current state-of-the-art IMU could achieve an

orientation accuracy of $5 * 10^{-3} [^\circ]$. This yields a 1100 m drift in the first hour. It was found that improvement in accelerometer precision does not yield better orientation estimation. However, an improvement in in gyroscope precision does yield better orientation estimation. Reducing the gyroscope measurement noise level down to $\sigma = 5 * 10^{-8}$ [rad/s] would yield orientation estimation accuracy of $5 * 10^{-5} [^\circ]$, resulting in a 11 m drift in the first hour.

No sensitivity towards the calibration time was found; however, these results seem unreliable as the performance for the 100 s period did not match with the other runs. This is assumed to be a coding bug that we could not solve within budget constraints; therefore, the calibration period results will not be further discussed.

The fact that the accelerometer precision is of little influence may be due to the fact that only one dimension is considered.

5. Conclusions

This paper investigated the potential of using quantum-based IMUs for the purpose of inertial navigation. This is particularly relevant for military use-cases, where it is likely that GNSS-based positioning methods are not available. In the first part, IMUs with quantum-based accelerometers and with significantly reduced measurement noise were considered. These sensors were used for the purpose of dead reckoning positioning. From a perfect starting point, with no error sources other than measurement noise, unknown residual misalignment was added in the accelerometer's measurement axes. An initial orientation error was also considered. It was found that both these error sources can have a detrimental effect on the strongly improved performance (with a measurement noise a factor 10–100. lower than a baseline FOG IMU). Improvements in other sensor characteristics cannot be exploited if the effects of these major error sources, present in all IMUs, are not mitigated.

In the second part, it was investigated how the effects of these major error sources could be mitigated. The problem was reduced to one dimension, and the equivalent to pitch/roll error was considered. A velocity sensor was added to the INS, previously only based on an IMU, and a DAI procedure was proposed. In this procedure, the vehicle covers a track, and the resulting dead reckoning velocity estimate is optimized through varying the estimated lumped axes' orientation angle error. After the most likely initial orientation angle is found, the vehicle may continue navigation without the presence of a velocity measurement, relying solely on inertial navigation. With high-quality (quantum) IMUs, the accuracy of a state-of-the-art DVLs may be achieved during this post-DAI inertial navigation period. This would reduce the need for the availability of GNSS while providing similar positioning accuracy and resulting operational capability, ultimately extending military operational capability in hostile environments.

6. Future Work

Future research will include more simulations, as well as more realistic sensor characteristics, including, but not limited to:

1. Colored noise;
2. Bias and bias stability;
3. Analysis in terms of Allan variance;
4. Scale factor and stability.

The above hold for conventional as well as quantum sensors. Modeling of cold atom interferometers (CAIs) and nitrogen vacancy-centers (NV-centers) and their characteristics could also be performed:

1. NV-centers [4]:
 - (a) Low noise;
 - (b) Not bias free;
2. CAIs [3]:
 - (a) Slow frequency/batch-wise measurements;
 - (b) Bias-free;

(c) ‘High’ noise.

Furthermore, the analysis will be extended to depict in detail the error buildup, in terms of Allan variance [1,14]. The new analysis will consider the problem in three dimensions instead of the current one-dimensional approach.

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