Flight Tested Results & Performance Analysis of a Machine Learning Software-Enhanced Inertial Navigation System†

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Abstract: In this paper Flare Bright presents flight test results gathered using a 1.2m wingspan fixed wing drone to demonstrate the capability that has been achieved using an Inertial Navigation System (INS) augmented by Machine Learning tuned software. INSs, using Inertial Measurement Units (IMUs), are invaluable for position estimation in GNSS-denied environments as no external information is required. However, with no absolute measurement of a vehicle's position or attitude, INSs suffer from significant drift over time. Flight test results show how Flare Bright's patent pending technique boosts the performance of an inexpensive mobile phone IMU by a factor of 200 over a 15 minute flight, creating an effective low cost and low weight INS for extended flight operations of small uncrewed aerial systems in GNSS-denied environments with similar performance to that with heavier high-end IMUs. Simulation data is used to provide a broader assessment of the capability by examining its application to high-end IMUs, with results demonstrating the potential value of Flare Bright's system within integrated navigation management systems across the wider industry.

Keywords: GNSS-denial; inertial navigation; machine learning; uncrewed aerial systems; flight test

1. Introduction

Flare Bright has developed a patent pending Machine Learning (ML) augmented software system that boosts the performance of simple and inexpensive Inertial Measurement Units (IMUs) for use within Uncrewed Aerial Systems (UAS) – Flare Bright's Software Enhanced Navigation System (SENS).

IMUs, composed of three-axes gyroscopes and accelerometers, are the foundation of Inertial Navigation Systems (INSs) across the aviation industry, with measured angular velocity and linear acceleration data used to estimate the aircraft's position and orientation from a known starting state [1]. INS is 'self-contained' [1], in that the system neither transmits nor receives any external signals. This makes INS an invaluable redundant system for UAS, and other aircraft, when Global Navigation Satellite System (GNSS) signals, typically used as the primary navigation system on aircraft, are lost, interfered with or spoofed [2] – note, GNSS is used here to refer to any satellite based navigation system.

UAS are increasingly being deployed in GNSS-denied environments, whether in defence contexts in conflict zones or commercially for operation indoors, such as within warehouses or tunnels, or in urban canyons where the presence of buildings can shield signals [2-4]. In the absence of GNSS signal, default operation reverts to an automated 'return to home' functionality or necessitates manual control [2], greatly limiting UAS use

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cases with GNSS denial increasingly responsible for accidents within the industry [5]. As UAS use increases [6], and GNSS-denial threats start to extend across the aviation industry beyond specific operation in known GNSS-denied use cases [7], there is a need for capabilities that enable accurate in-flight position tracking in the absence of GNSS signal, or indeed any radio communications.

An INS using IMUs alone cannot meet this requirement due to significant position estimation drift over time. This occurs as there is no absolute measurement of the aircraft's position or attitude, resulting in sensor inaccuracies creating navigation errors that cannot be corrected [1, 4] – due to the mathematical integration required, the navigation position growth rate is at least quadratic with time, and in practice typically cubic or higher due to the fusion of gyroscope data with accelerometers [1]. High-end 'navigation-grade' IMUs, deployed on large aircraft, provide the accuracy required over practical flight scenarios, but are too expensive, heavy and power hungry to meet the requirements of many, particularly smaller, UAS. Visual navigation systems such as SLAM, integrated with an IMU, provide a means of correcting for IMU drift, but in turn have limited accuracy in visually homogeneous or degraded environments, rely on camera quality, can be computationally intensive and adversely impacts weight and power requirements of the sensing unit [4].

In this paper, flight test and simulation results are presented to demonstrate how Flare Bright's SENS may be used with low cost, low power and low weight IMUs to provide an INS with a degree of accuracy suitable for extended flight operations for small UAS, without the limitations of typical visual based navigation systems. For this research the baseline IMU is a 'consumer' grade sensor, InvenSense ICM20948 (note, IMU classification is defined in [8]). The range, and limitations, of tests conducted will be introduced and the flight test data will be analysed to show the performance achieved in real world deployment of SENS on a prototype UAS. Finally, simulation data will be used to explore the capability in scenarios beyond what is currently achievable in real-world test. In this way, this paper will demonstrate how SENS may enable the application of low cost IMUs to provide redundancy to higher end sensors or enable the augmentation of high end sensors beyond current capability, providing value to both UAS and the wider industry.

2. Methodologies

SENS has been flight tested using Flare Bright's demonstrator drone platform, the Persistent Autonomous Drone (PAD). SENS has also been tested in simulation using Flare Bright's Machine Learning optimised Digital Twin of PAD. In this section, key aspects of the methods deployed are summarised.

2.1 Core Concepts

An INS is composed of a sensor, i.e. the IMU, and a computational unit that performs the necessary calculations, typically through the use of advanced Kalman filters, to estimate position and attitude [1, 8]. In this work, Flare Bright's INS solution uses in-house Kalman filtering algorithms optimised to process the ICM20948 IMU data.

Like any INS, SENS too relies on tuned computational algorithms, including Kalman filters. Details of the proprietary SENS algorithms are beyond the scope of this paper for reasons of commercial sensitivity. Importantly, like any INS, SENS is baselined and optimised 'offline' and does not employ any ML during flight. Therefore, SENS performance is deterministic, at a given version, set only by relevant sensor readings it is supplied with.

2.2 Flight Test Data Gathering

Flare Bright has developed a 1.2m wingspan flying wing demonstrator UAS using a Horizon Hobby Opterra-1.2 airframe with Flare Bright electronics and software, known as PAD (shown in Figure 1). PAD provides a means of testing out different Flare Bright software capabilities, as they are developed, on a platform that can be flown within a reasonably light touch, albeit constrained, regulatory framework - the UK Civil Aviation Authority's Open Category Restrictions for Unmanned Aircraft Systems [9].

Four flight test data sets have been examined to showcase the SENS capability versus the navigation performance of the baseline INS using PAD: a single 1 minute flight; a single 2.5 minute flight; a single 5 minute flight; and a single 15 minute flight. Note, these flight times are representative, and not exact, values of the actual times flown.

Figure 1. PAD on its stand for final system tests prior to a hand launch for flight.

Each flight was composed of circular orbits of approximately 50 m radius at a level altitude of ~15 m above ground level and roughly constant airspeed of ~16 m/s. All flights were conducted under human piloted remote control as the risks of navigation drift, and the impact on autonomous control, are unacceptable within the tight confines of the limited ground and airspace available. Flight tests to date have been limited by acceptable weather windows over winter and test site availability.

2.3 Navigation Data Replay using Digital Twin

To get the most out of the flight test data collected, Flare Bright's "navreplay" tool has been used. The "navreplay" tool enables flight sensor telemetry data, logged during flight, to be fed back through the navigation system offline, using a standalone instance of the navigation system to write a new navigation state estimate to another log – this works because the navigation algorithms are deterministic (Section 2.1). By configuring the standalone, offline, navigation system differently to how it was in the actual flight (i.e., with or without a given feature on), it is possible to see how the system would have performed if it had been configured this way. Therefore, the actual navigation performance for SENS can be compared to the performance of the reference INS on the same hardware and in exactly the same flight conditions. The tool has been deployed as follows:

- 1 minute flight: Flight conducted in 'INS' mode, and "navreplay" applied to generate SENS performance prediction from the telemetry data post-flight.
- 2.5, 5 and 15 minute flights: Flights conducted in 'SENS' mode, and "navreplay" applied to generate INS performance prediction from the telemetry data post-flight.

As the INS performance is known, conducting the longer flight tests with the software configured to operate in SENS mode, rather than INS mode, ensures a clear-cut capability demonstration with no question marks over the accuracy of the "navreplay" tool.

2.4 Simulated Flight Test in Synthetic Environment

Simulated assessments of the SENS capability require two modelling considerations: flight scenario simulation and IMU emulation.

Simulated flight scenarios consisted of level altitude, straight line, flight paths, held at a roughly constant airspeed of 16 m/s over 60 minutes. Simulations were run as batches of 20 flights to generate statistically relevant evidence associated with individual test scenarios. The simulations applied random, albeit constant, mean wind states during the flight, superimposed with a Dryden based atmospheric turbulence model. The flight control was modelled independent of the navigation estimation system to avoid feedback between the choice of navigation estimation system and control response.

For this work, 6 different IMUs were considered covering a range from low end consumer-grade (ICM20948) through industrial (MTi-3) and tactical (HG1700, ILK220, SBG Pulse-40) sensors to an exemplar navigation grade sensor (HG9900) - for context, the HG9900 is nearly 4000 times heavier, draws 2000 times more power and fits in a volume nearly 400,000 times larger than the ICM20948. The data simulated for each IMU is summarised in Table 1, based on data freely available from product datasheets [10-15] or, in the case of the reference ICM20948, based on in-house tested performance. IMU random walk errors are converted to a standard deviation to define a normal distribution of IMU noise and is sampled at each simulation timestamp. IMU bias is also converted to a standard deviation to define an error normal distribution, from which a constant error value is randomly applied for each flight in the batch. In the simulations, these 'virtual' IMUs replace the real IMU data, in the manner described in [1], as inputs within the same optimised INS and SENS computational algorithms that have been flight tested (Section 2.2).

Table 1. Datasheet specifications of IMU (gyroscope and accelerometer) biases and bandwidths, and IMU frequency for the different modelled systems.

IMU Name	Gyroscope			Accelerometer			Frequency (Hz)
	1σ Bias (°/hr)	1σ Random Walk (°/√hr)	Bandwidth (Hz)	1σ Bias (mG)	1σ Random Walk (ms^{-1}/√hr)	Bandwidth (Hz)	
ICM20948 [10]	596.00	3.415	10	6.52	0.77790	10	200*
MTi-3 [11]	10.000	0.420	230	0.03	0.07056	230	1000
HG1700 [12]	0.250	0.125	100	0.05	0.01980	100	600
ILK-220 [13]	1.000	0.200	260	0.005	0.01500	260	2000
SBG Pulse-40 [14]	0.800	0.080	480	0.006	0.02000	480	2000
HG9900 [15]	0.0006	0.002	100#	0.01	0.01980#	100#	600#

* ICM20948 frequency can be up to 9 kHz (gyro) or 4.5kHz (accelerometer) [10], but Flare Bright run at 200 Hz. # Data copied from HG1700 data sheet due to lack of availability.

Two underpinning assumptions may be limiting as simulated flight time increases:

- The constant mean wind state approximation becomes unrealistic over long flights or through different environments. Depending on how significantly the wind changes in flight, this may be a large error contributor to the SENS capability, and therefore the simulated results presented in this report are over-estimates of the navigation performance. Note, this approximation has no impact on INS performance.
- The IMU bias should strictly be modelled as varying over the flight duration, rather than treated as a constant. The approximation will lead to a lack of physical realism for INS navigation estimates over longer flights, and by extension also impact SENS performance estimates. Nevertheless, the standard deviation approach provides a simple approximation and is considered appropriate for the flight durations assessed here in the context of a batch of simulated flights.

Note also, the INS and SENS algorithms have been optimised for the baseline ICM20948 and, for the purposes of this simulation study, have not been re-tuned against the metrics of the new IMUs. This enables a consistent simulation evaluation, but also implies, for the new IMUs, that simulated performance may be underestimated.

3. Flight Tested Performance Assessment

The navigation position estimation error results from the flights are shown in Figures 2a-d, in order of increasing flight time from 1 to 15 minutes – the scales on the figures are different to ensure data can be visualised clearly for comparison in each case. The position error plotted in Figures 2a-d is evaluated as the difference between the SENS, or INS, position estimate versus the GPS track of the aircraft, which is treated as the ground truth.

The results in Figures 2a-d demonstrate very clearly that the impact of using SENS is to change the navigation estimation error response such that it may be approximated as a linear error growth rate in position estimates. This linear growth rate, in all cases tested, is significantly smaller than the approximately cubic error growth rate seen with the standard INS data. Note, in Figure 2c the INS result shows a strange kink approximately 250 seconds into the flight, although the overall performance is consistent with that seen across the other flights for the baseline INS system. This anomaly has been attributed to telemetry log gaps preventing a clean replay of the telemetry for this period using the "navreplay" tool (see Section 2.3) and is not considered significant.

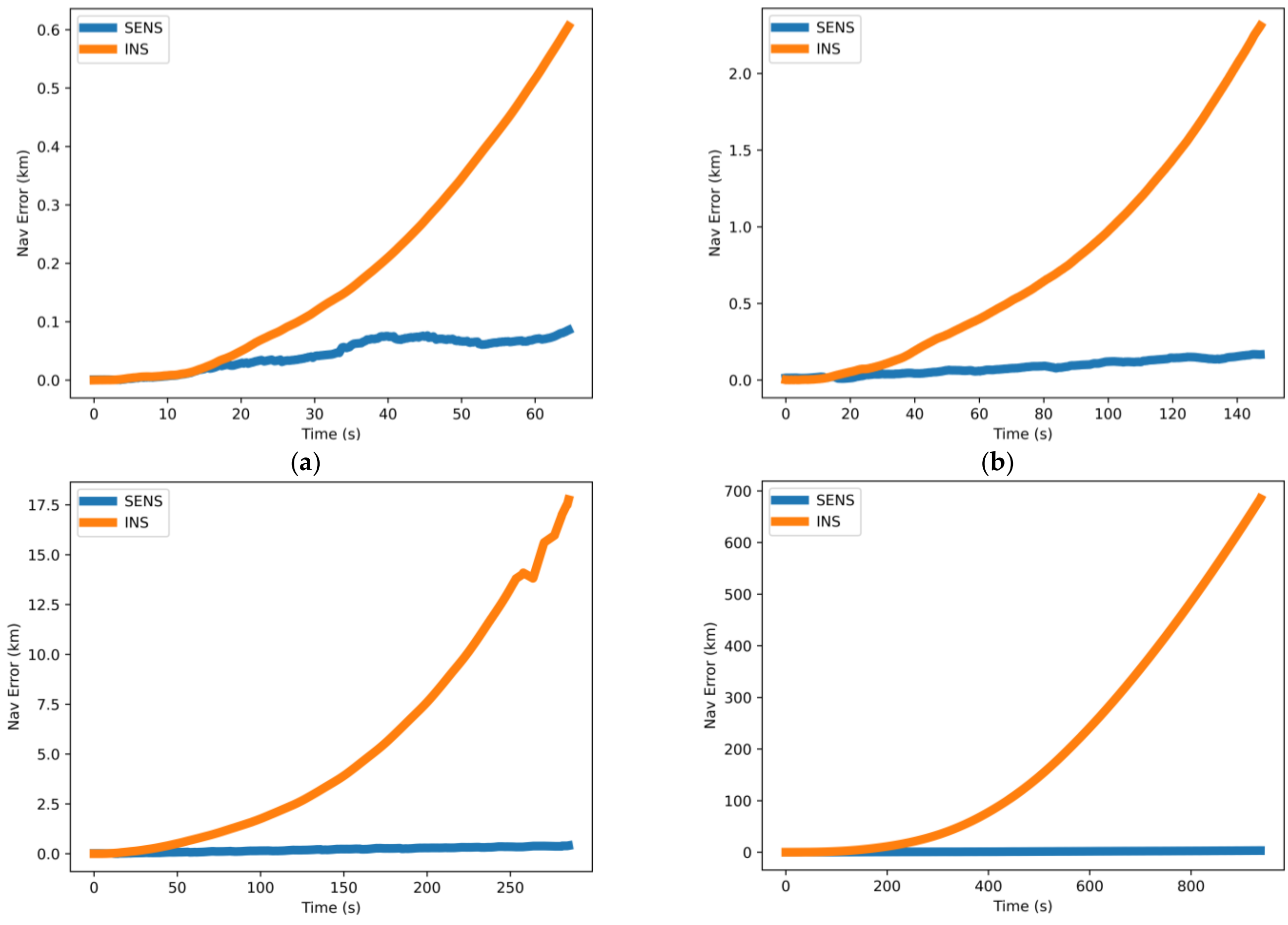
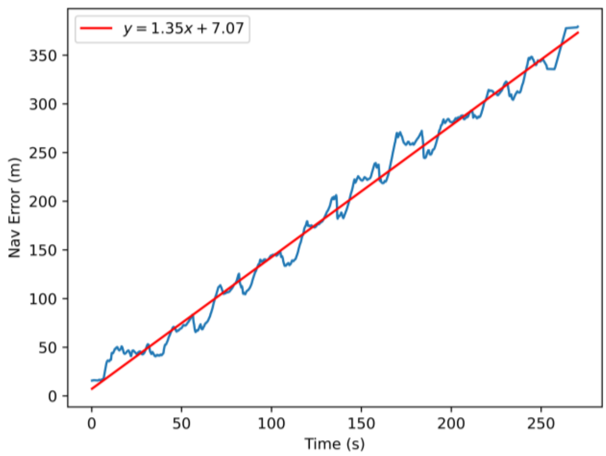


Figure 2. Navigation position error estimates over flight time for manually piloted flights (scales different for different flight times), comparing baseline INS error (orange) with SENS error (blue): (**a**) 1 minute flight; (**b**) 2.5 minute flight; (**c**) 5 minute flight; (**d**) 15 minute flight.

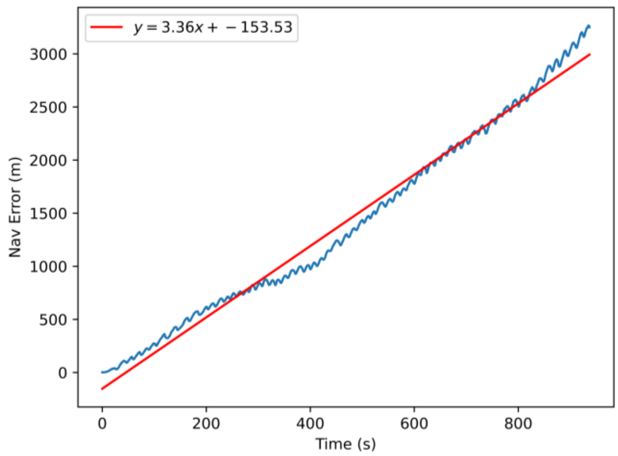
The SENS navigation position estimate errors are replotted for the 5 and 15 minute flights in Figures 3a-b respectively, superimposed with a line of best fit in red, with different vertical scales that show the nuance of the navigation performance more clearly. The results shown in Figure 3 indicate an oscillation about the line of best fit, believed to be due to the effect of orbiting flights and error sources cancelling out, for example by operating alternately in tail or headwinds as the orbit is completed. Due to limitations to space available for flight test activity, both due to site availability and the regulations in place, it is not yet possible to complete flight tests in extended straight lines that would help understand the significance of this feature. The effect is removed in the simulation results presented in Section 4 by simulating straight line flights.

The results of the flight tests are summarised in Table 2 in terms of the linear SENS growth rate observed and the factor of improvement over the final navigation position error using SENS with respect to the baseline INS solution. Two key observations are:

- The factor of improvement increases significantly with flight time due to the approximately cubic growth rate associated with the baseline INS, such that after the approximately 15 minute flight a factor of improvement of more than 200 is observed.
- Although SENS results appear linear, the lines of best fit for each case present a large range of linear error growth rates, not correlated with flight time. Referring to Figures 3a-b, it is possible to say that the error growth rate is constant for the shorter 5 minute flight window (Figure 3a), but changes (increases in this particular case) over the course of the longer 15 minute flight (Figure 3b) – this could be contributing to the variation in Table 2. Although it is difficult to draw a firm conclusion on performance variation from the limited flight data available, from a detailed, simulation based, error analysis of SENS, outside the scope of this paper, it is believed that the driver of this variation is most likely changing wind conditions between and during flights.



(a)



(b)

Figure 3. SENS navigation position error estimates over flight time (scales different for different flight times), with linear regression superimposed (red line) (**a**) 5 minute flight; (**b**) 15 minute flight.

Table 2. Flight test SENS performance summary

Flight Time (s)	SENS Growth Rate (m/s)	Factor Improvement vs INS
65	1.80	5.2
150	0.94	15.2
290	1.35	45.3
940	3.36	209.5

INS and SENS performance results measured in flight tests have been used to verify the simulator performance for the reference IMU, within the realm of what is possible with the limited flight data. For brevity, the results are not discussed in detail here, but an example INS case, corresponding to data in Figure 2d, is shown in Figure 4 versus a histogram of navigation error from a batch of 100 simulated flights – Figure 4 supports the validity of the simulation capability as the flight data matches simulated expectations.

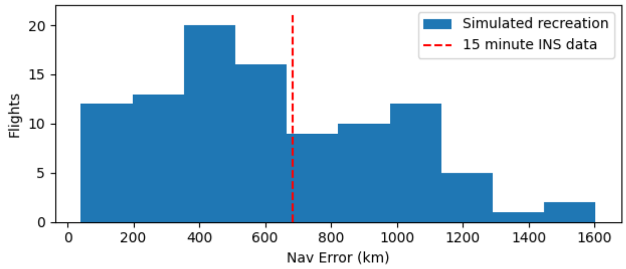
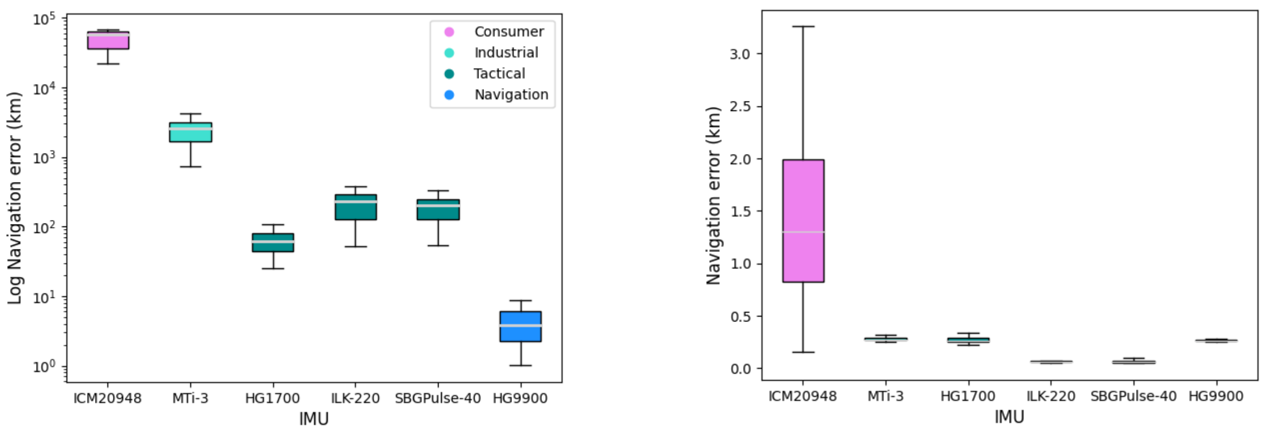


Figure 4. INS navigation error estimate from 15 minute flight test versus a histogram of error estimates from 100 simulated flights seeded randomly to represent baseline IMU errors (Section 2.4).

4. Beyond the Current Use Case: Simulation based Capability Analysis with High-end IMUs

On small UAS, where power, weight and cost are critical, consumer grade IMUs, such as Flare Bright's reference ICM20948, are widespread – for example in the widely used Cube Orange+ flight computer [16]. Such IMUs are unlikely to ever be used for larger UAS, or on crewed aircraft, where accuracy, reliability and robustness of the sensors are paramount to ensure flight safety and to comply with certification standards. In this section, simulation data is used to examine the likely performance of SENS when used with a higher end IMU, of the form used more widely across the aviation sector. Note, the simulations are not expected to be an exact benchmark of the performance with each IMU due to modelling limitations outlined in Section 2.4, but should be representative of the likely performance gain from switching to higher end IMUs and applying SENS.

The navigation position estimate errors from batch simulations are shown in Figures 5a-b for the INS only solution and for the SENS capability respectively, by considering the representative range of IMUs tabulated in Table 1. The results in Figure 5a are within reasonable expectations of practical INS performance based on characteristics of the IMUs (Table 1) and product expectations [10-15]. As expected, Figure 5a confirms that the performance is greatly improved as the IMU quality increases (note the log scale in the y-axis). In comparison, for every IMU the results in Figure 5b show that the SENS flights have significantly less navigation error (note the different y-axis) than the corresponding INS only (Figure 5a) scenarios.



(**a**) (**b**)

Figure 5. Simulated navigation position error after 60 minute flights for representative IMUs, where the orange line represents the median value and the box demarcates the upper/lower quartile of the batch of results for (**a**) INS only (note, log scale in y-axis); (**b**) SENS (different y-axis range).

Interestingly, Figure 5b indicates that the SENS improvement achievable has diminishing returns with improving IMU quality – that is, after the approximately 5x reduction in error from the ICM20948 to the MTi-3, the median error across the batches is not greatly reduced when changing IMU, although the spread of error does shrink marginally. It is possible that this diminishing effect is an artefact of the fact that the SENS system has not been optimised for the performance of each of the simulated IMUs (see Section 2.4).

A further parameter worth considering is the 'cross-over' point. As shown in Figure 2, SENS changes the nature of error growth from the approximately cubic growth rate associated with the baseline INS solution to a linear growth rate. Mathematically there is therefore a point at which the two results 'cross-over' (not visible from the scales in Figure 2) and the SENS navigation position error starts to be lower than the baseline INS estimate. This cross-over point is consequently important as it determines the flight time after which using SENS with a given IMU is valuable. The average cross-over flight times for the simulated batches are shown in Figure 6 for each IMU investigated. As expected, the cross-over point increases significantly as the quality of the IMU improves, such that, within the modelling limits indicated in Section 2.4, SENS is shown to prove useful with the HG9900 only after approximately 3 minutes of flight compared to the near immediate positive impact observed with the ICM20948.

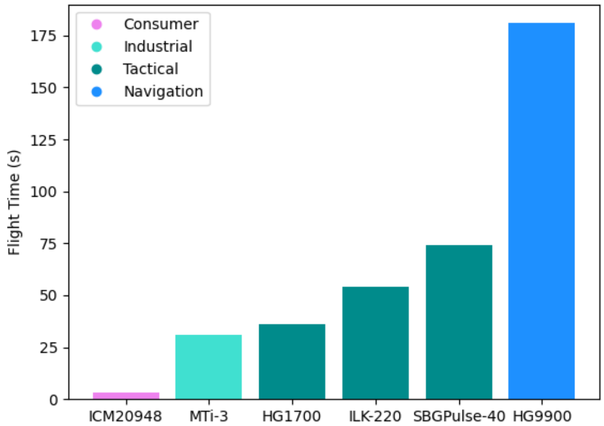


Figure 6. Cross-over flight time at which point SENS begins to outperform the baseline INS solution for the range of IMUs simulated.

5. Conclusions

Flight test results of Flare Bright's GPS free software enhanced inertial navigation system, SENS, have been shown to demonstrate the current SENS capability achieved using a consumer grade IMU on a 1.2m wingspan fixed wing drone. The results from these orbiting flights show a significant improvement, translating to around 200x increase in navigation position accuracy over the performance of a traditional INS system using the same hardware over a 15 minute flight window. These results demonstrate that it is possible to reduce the size, weight, and power requirements of an inertial navigation system, without compromising on navigation accuracy, by using SENS with a low-end IMU.

Furthermore, an investigation into the impact that using a higher quality IMU has on SENS's performance was completed using simulations. The results from this assessment show that improving the quality of the IMU, over the current consumer grade sensor used on the demonstrator platform, will significantly improve the navigation performance of SENS by at least a factor of 5 in the scenarios simulated.

Therefore, by introducing redundancy and increasing accuracy in flight safety critical systems without adding significant size, weight or power penalties, SENS can be widely applicable within integrated navigation systems on a wide range of aircraft and may provide a route significant cost savings in terms of fuel and range.

6. Next Steps: Future Research and Exploitation

The commercial value of replacing expensive IMUs with software is significant, particularly for small, payload and cost limited, UAS platforms or UAS platforms and UAS-type projectiles/munitions that are either single use or are likely to have a limited lifespan. The work presented in this paper demonstrates a proof of concept navigation capability that provides a route to exploiting the gap in the market.

Since the presentation of this data at the ENC 2023, further exploitation and demonstration on PAD and other UAS platforms has been undertaken as part of follow-on projects, including within more realistic operational environments. Further work is required to assess this data gathered, and to assess the consistency, operational restrictions and error sources involved when the capability is deployed on alternative UAS platforms, including multi-rotors, and UAS-type vehicles, including loitering projectiles/munitions. In particular, it would be beneficial to investigate a wide range of practical results from flight trials of this IMU augmentation to complement the assessments completed in simulation. There is also a wider piece of work that should be undertaken on the practical validation of the simulation results with different IMUs, not just different vehicle platforms.

Another important area of future research is ascertaining the "hand-off" procedures in the navigation stack. With increasing vulnerability of GNSS systems, and challenges with other methods of navigation, such as visual navigation where bad weather and featureless terrain such as deserts limit accuracy, it is likely that multiple methods of navigation would be beneficial from a redundancy perspective. Work is needed to understand which system is the best truth at any point in a journey and what is the procedure for handing off between one system and another.

7. Patents

The capability demonstrated in this paper uses a proprietary Flare Bright technique, filed as a patent entitled "Fluid flow estimation and navigation" on 25 August 2022.

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