Proceeding Paper

Flight Test Performance Assessment 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 ~2m fixed wingspan 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-compromised 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. The results from a robust flight test programme, over multiple vehicles, terrains and flight paths, show how Flare Bright combined a low cost and low SWaP (space, weight and power) IMU, with their patent pending software-only techniques, to boost INS performance to the degree of besting a 'tactical grade' IMU in ~20 minutes. These results credibly demonstrate the value of Flare Bright's solution as an effective, low cost and low weight, INS for extended flight operations of small uncrewed aerial systems in GNSS-compromised environments, with performance comparable to heavier, more expensive high-end IMUs.

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

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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 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 navigation position 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 (see [8] for definitions of different IMU grade classifications), 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].

At last year's ENC conference, Flare Bright introduced the novel SENS concept, supported by preliminary flight test data on a small prototype test-bed [9]. In this current paper, Flare Bright will present extensive and varied flight test results to demonstrate the credibility of its software solution deployed on an aircraft not designed or controlled in-house. 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. Results will be compared with past performance achieved on a different platform and will be commercial contextualised by comparing the performance of recognised, widely used, high-end inertial sensors. In this way, the paper will demonstrate how Flare Bright's SENS may be applied to low cost and low SWaP (size, weight and power) IMUs to provide a pure INS solution (i.e. no visual or other alternative navigation solution) with a degree of accuracy appropriate for extended flight operations for small UAS.

2. Methodologies

This section will cover the core technology understanding required for the flight test analysis. It will also introduce the platform used for this series of tests, the deployment strategy employed for SENS and the data collected for the performance assessment.

2.1 Overview of Flare Bright's SENS Technology

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 Kalman filters, to estimate position and attitude [1, 9].

Like any INS, SENS too relies on tuned computational algorithms, including Kalman filters. In addition, SENS relies on core Flare Bright, patent pending, technologies including a highly exquisite, ML optimised, Digital Twin (DT) of the platform and a flow-based estimation and navigation algorithm. The DT is at the heart of Flare Bright's technology, enabling rapid tuning of the algorithms for optimal performance, and, when embedded on board the aircraft, enabling a simulated understanding of how the vehicle should fly to be interrogated during flight. The core SENS algorithms critically are designed to operate in the absence of GNSS data streams.

Flare Bright uses a physics-based approach to generate DTs. First, a "modelling" stage is used to create a baseline twin based on design or bench test measured data. Second, a "calibration" stage is conducted where flight tests exploring various manoeuvres, such as rotations in each axis and (de)accelerations, are completed. Only a few seconds of data for each manoeuvre has been found sufficient to use ML to tune the DT to a point where it has been verified to perform as an accurate representation to the real-world platform in simulation.

Details of the proprietary core SENS algorithms are beyond the scope of this paper due to commercial sensitivity. Importantly, like any INS, SENS is baselined and optimised 'offline' and does not employ any ML during flight. This enables the SENS performance to be deterministic, at a given software release version, for a given set of sensor readings.

Note, where this work refers to generic INS results as comparisons against SENS data, the INS data is generated using the same optimised Kalman Filters as SENS.

2.2 Flight Test Platform

The UAS platform used for this flight test programme is CATUAV's ATMOS-8, pictured in Figure 1. This is a 2m fixed wingspan aircraft, with a maximum take-off weight of 3.3kg. The flight controller deployed on the platform is a Cube Orange [10], and the aircraft is equipped with a Raspberry Pi 3b [11] to enable test software to be deployed on the vehicle for the purposes of research activities. No cameras or visual systems were installed on the platform during this flight programme. Two aircraft were built to enable robust reliability testing of SENS performance by comparing results between the vehicles.

Figure 1. The two CATUAV ATMOS-8 platforms used as flight test demonstrators for this work.

2.3 Deployment of SENS on the Test Platform

The ideal SENS deployment is as a software only package, integrated directly into a flight controller for the platform. However, for this to happen, the flight controller is required to have a Linux based OS with suitable processing and RAM capabilities. Since the Cube series is based around a microcontroller, this type of deployment is not possible. Instead, Flare Bright deployed SENS onto the Raspberry Pi 3b, which was already available on the ATMOS-8 as a companion computer to the Cube Orange.

Note, for the duration of this test programme, SENS was operated in a "passive" or "sandboxed" mode. This means that while SENS received all the data required to produce a navigation solution, it did not return that solution to the Cube Orange. It simply logged the input data and resultant navigation solution for analysis after the flight.

2.4 Approach to Flight Test Data Gathering

The test programme was conducted in a partnership with BCN Drone Center, who are based out of Barcelona, Spain. BCN Drone Center operates an airfield for various drone testing requirements and are also the hosts of the ATMOS-8 platform. This test programme had two different flight areas; BCN Drone Center itself and over the sea near Platja de Murta, Barcelona. The over sea flights were specifically chosen to showcase SENS working in a situation visual navigation would fail - a featureless ocean surface. Note, for the purposes of this work, the UAS was flown under specific EASA permissions granted to Flare Bright collaborators, BCN Drone Centre.

The planned flight paths for these locations are shown in Figure 2. The paths presented are just representations of the real flight paths, since these required translation into orbit or waypoint missions when plotted in the GCS software used to manage the Cube Orange. Each test was conducted at ~40m AGL, where ground level was defined as the runway for tests at BCN Drone Center and the sea level for tests at the beach. Due to regulatory restrictions, no jamming or spoofing of GNSS was active during flights, which means GNSS data (provided by a standard Here2 module) was available for autonomous navigation and ground truthing, while SENS was run 'sandboxed' logging its position estimate separately. Flights were conducted with cruising speeds of ~17m/s and varied in time from ~15 minutes through to just over an hour. The flights formally included as part of the test programme were made up of 6x orbits, 4x race tracks and 4x over sea flights.

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

Figure 2. Layouts of automated flight paths flown during the test programme: (a) Orbits: A 300m orbit (blue); (b)Racetracks: A racetrack formed from 1.5km long stretches spaced 200m apart (blue); (c) Over-sea: Flight path (purple) constrained by regulatory limits to the extended visual line of sight activity over the Mediterranean Sea near Sant pol de Mar.

At the time these tests were conducted, SENS only used a single 9 axis IMU data stream (comprised of a 3-axis accelerometer, 3 axis gyroscope and 3 axis magnetometer) from the Cube Orange. Additionally, the foundational DT that enables SENS was also updated with messages relevant to the current state of the control surfaces and thruster. While IMU and actuator state data is the only required baseline input to SENS, and SENS can function with just that data, the navigation performance can be boosted further by also consuming a variety of other common sensors, such as a pitot tube which was used on the ATMOS-8. Wherever possible, Flare Bright also collects atmospheric data during tests, both to understand any errors that may come up and to aid in the recreation of the flight tests in simulation if required. BCN Drone Center, where most tests were conducted, had a weather station that could record wind speed and direction, temperature, atmospheric pressure and humidity.

3. Flight Tested Performance Assessment

This section will explore the SENS performance across a variety of flight times, flight paths and aircraft. The focus of this assessment will be to confirm a key performance characteristic of SENS: the ability to take the normally quadratic, or worse, navigation error growth of an inertial navigation system, and replace it with an approximately linear error growth. “Navigation error” is defined as the difference between an alternative navigation solution’s position estimate (either that of SENS or the pure INS result), and the “ground truth” position given by the Here2 GNSS module.

Historically, Flare Bright has attempted to demonstrate the performance of SENS by comparing it to a pure INS solution with identical input data [9]. This was a useful comparison since most flight times were in the 1-5 minute range, where the INS performance, for the baseline low-cost consumer grade IMUs used, would be reaching its absolute limits. SENS could then showcase how it overcomes those performance limitations and enable a platform to survive a GNSS dropout for that length of time.

Figure 3 shows a plot like this for one of the hour-long flights conducted during these trials. While this remains a useful plot to show the scale of improvement SENS can achieve (in this case a factor of ~2700 over the baseline INS solution), ultimately over the flight times seen in this series of tests, it's not a fair or realistic plot; if the 1-5 minute flights conducted historically were going beyond normal INS capabilities, comparing it over an hour-long flight becomes entirely meaningless. The scales required for these plots are also misleading as, in comparison to the higher than quadratic error growth observed with by the baseline IMU, SENS appears to have no growth in navigation error, which is incorrect.

For the remainder of this paper, INS results in this form will be disregarded for the baseline low-cost IMU and the SENS performance will be analysed in isolation.

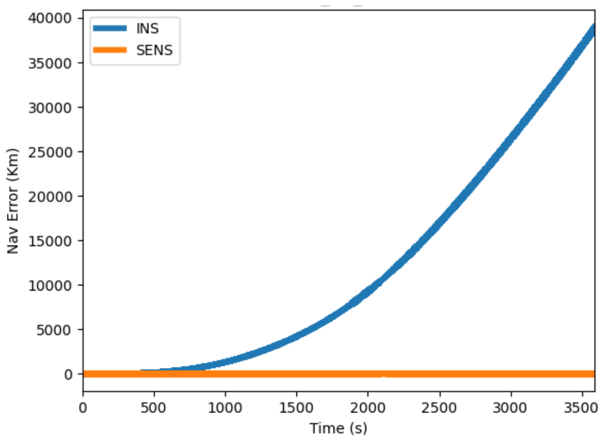


Figure 3. SENS navigation error (orange) compared to the baseline INS navigation error (blue) over an hour-long flight. Due to the nature of error accumulation, the INS error grows rapidly, at quadratic (or higher) rates, to values that are no longer credible. The SENS solution negates this effect.

To provide a credible value offering, the SENS capability must be repeatable across different conditions, including flight times, flight paths and aircraft. Figures 4-6 will examine these cases by plotting the SENS navigation error growth from flight test data (blue) against flight time. Three factors, seen in these figures, are considered important when examining the ability of SENS to linearise error growth:

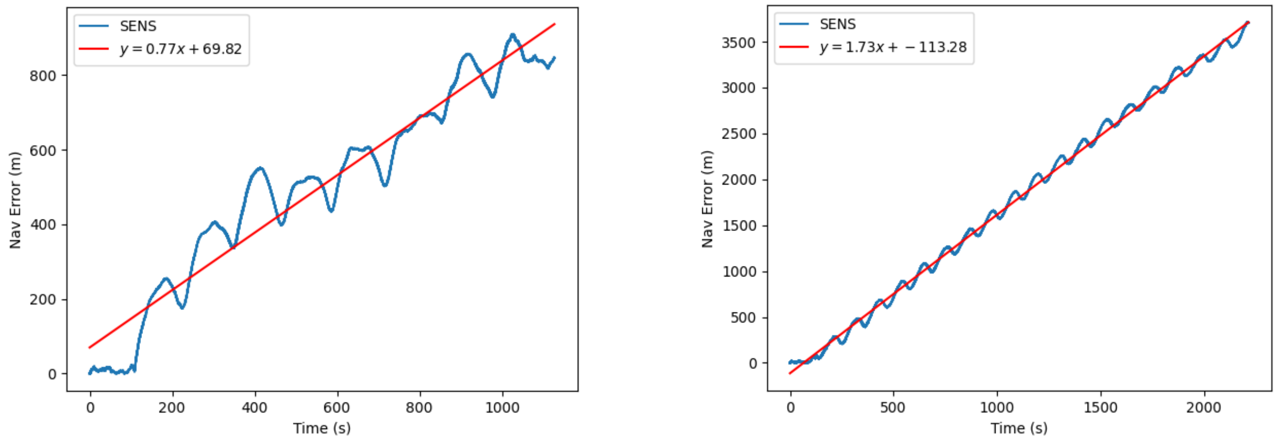
- Firstly, a line of best fit, calculated using standard linear regression, will be superimposed, in red, onto each plot of flight test data. This will confirm linear error growth.
- Secondly, the gradient of the line of best fit, which can be found in the graph legends, are not quite identical across any flight – this is discussed later in the section.
- Finally, each graph shows a minor oscillation pattern, the shape of which is believed to be determined by flight path and the effect of flying into varying wind conditions.

Impact of flight time: Figure 4 shows a comparison of two orbiting flight paths (see Figure 2a) of different flight times, 17 minutes and 35 minutes respectively. Superimposed in red is a linear regression-based line of best fit. Figure 4 very clearly shows that, irrespective of flight time, the navigation error growth when SENS is used can be approximated to a linear line of best fit. The oscillations in nav growth are clearly visible in the result, and, although not exactly periodic, represent a simplistic repeating pattern that is approximately consistent with the orbit period.

Impact of flight path: Figure 5 shows an orbit flight path (see Figure 2a) and a racetrack flight path (see Figure 2b). These flights were 66 minutes and 61 minutes respectively. Figure 5 very clearly shows that, irrespective of flight path, the navigation error growth when SENS is used can be approximated to a linear line of best fit. The oscillations in navigation error growth are also clearly visible in the result. In Figure 5, due to the difference in flight path, the periodicity associated with the error growth oscillation appears different, but this does not have a quantifiable impact on the overall linear growth rate. Note, in this particular case, the gradient of the line of best fit is remarkably similar. Note also, by comparing Figure 5a with Figure 4, it is clear that even increasing flight time to an hour does not impact the overall linear approximation to navigation error growth.

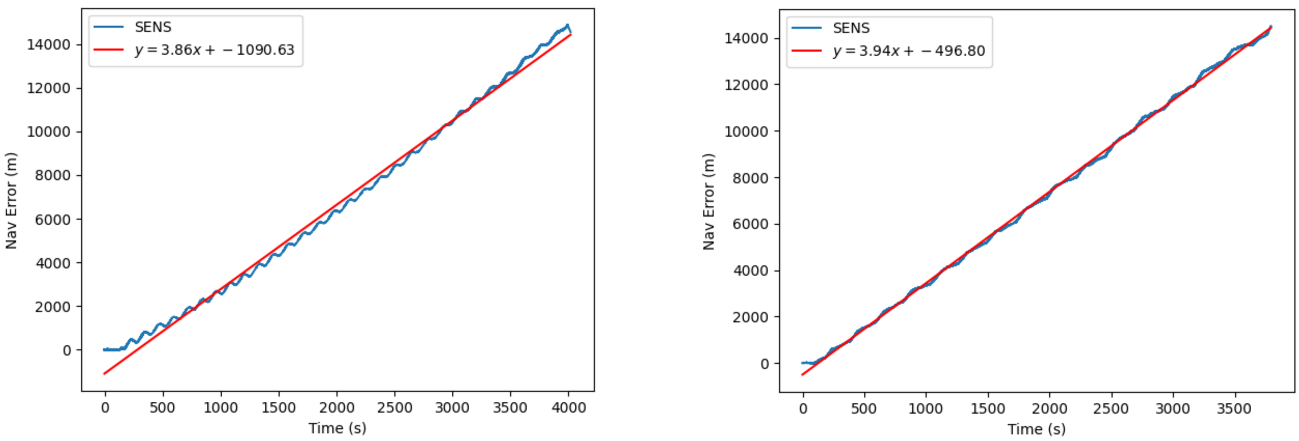
Impact of changing vehicles: Figure 6 shows a 34-minute orbit completed with a second ATMOS-8 platform. This can be compared with Figure 4b, which showed a similar

35-minute orbiting flight with the first platform. In both cases, the linear error growth is evident. On similar time scales, it is clear that the oscillation observed in the raw flight test results (blue) for both figures are the same, as would be expected given the aircraft were completing similar flight paths, albeit on different flight test days. It is possible to further assess cross platform consistency by comparing the current results with that from Flare Bright's preliminary flight test assessment whitepaper [9], where similar results were shown with a hobbyist flying wing UAS. The results confirm that the SENS linear error growth characteristic is consistent across entirely different platforms, including simplistic prototype UAS without additional sensors like the pitot tube.



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

Figure 4. SENS navigation position error estimates over flight time (scales different for different flight times), with linear regression superimposed (red line) (**a**) 17 minute flight; (**b**) 35 minute flight.



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

Figure 5. SENS navigation position error estimates versus flight time, shown for ~1 hour long flights over different flight paths, with linear regression superimposed (red line) (**a**) Orbit; (**b**) Racetrack.

Holistic view: Figure 7, collates the navigation error growth rates for all flights in this test programme as a function of flight time. This is plotted against the expected performance of SENS based on simulations that use the DT created for the model to fly. The simulations were conducted in representative conditions, e.g. matching wind speeds, pressures, even as far as matching the angles of the magnetic fields of the area the real flight tests were conducted in. Since there are too many simulation points to reasonably plot, the data is shown as the mean and 95th percentile error growth rates. Note, a discussion around Flare Bright's simulation capabilities is beyond the scope of this paper but a high level summary may be found in [9]. It can be seen that 3 flight test results lie almost exactly on the simulated mean line. The remaining results form a roughly even distribution about the mean. This shows two distinct facts; first, the results from this test programme are very consistent, with a standard deviation of ~1.22m/s; second, the simulator's prediction of in-flight SENS performance was very accurate, demonstrating the value of highly exquisite DTs for real world capability assessment.

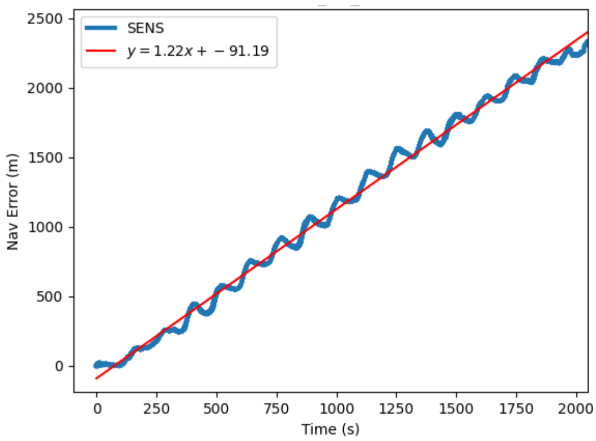


Figure 6. SENS navigation position error estimate versus flight time, shown for ~30 minute flight flown using the second ATMOS-8 aircraft, with linear regression superimposed (red line).

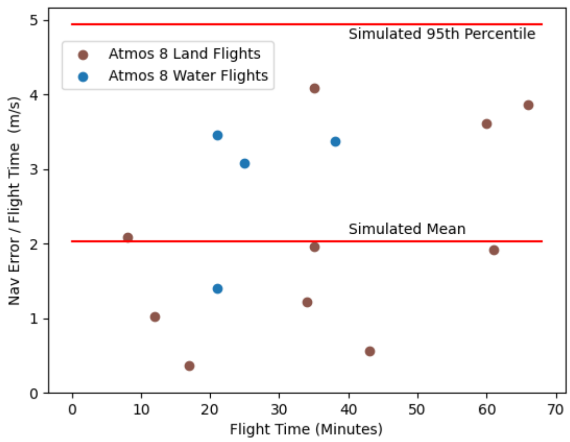


Figure 7. Flight data plotted in terms of linear error growth gradient against flight time, with results from hundreds of corresponding simulations superposed as mean and 95th percentile lines (red).

While flight test results and simulation line up, the spread of both is higher than ideal. Flare Bright has investigated the error sources that contribute to variations in error growth rates, using both simulation and flight test, and are actively addressing them as part of current projects. While a detailed discussion is beyond the scope of this paper, it is worth noting that algorithmic tuning, optimisation of the underpinning Digital Twin and making use of multiple IMUs (such as available on the Cube Orange), to reduce the impact of single sensor bias, are all means of achieving this aim.

4. How can SENS revolutionise the UAS industry?

The Flare Bright SENS value proposition is based around significantly boosting the INS performance of a low cost (~$5) and low SWaP consumer grade IMU. Figure 8 shows a SENS 1 hour long flight test result resulting in ~7km navigation error, which is representative of the average performance achieved over the flight test programme. In comparison, Figure 8 also shows the simulated performance of an INS-only system with a ~$10k tactical grade IMU (purple) and ~$100k navigation grade IMU (red), representative of the advertised performance of the HG1930 [12] and HG9900 [13] respectively - the navigation error after an hour is ~19km and ~1.5km with these IMUs respectively. For details of the approach to simulating the INS-only performance refer to [9].

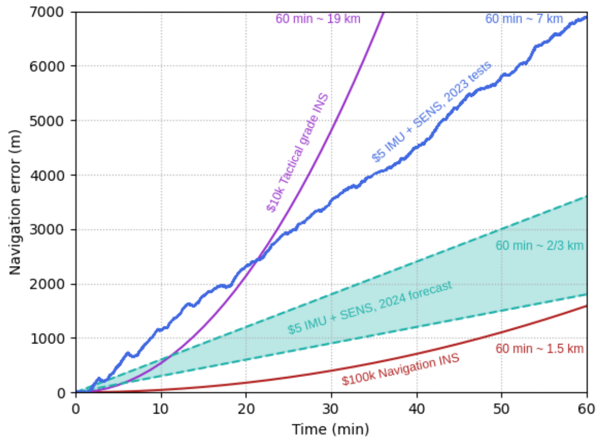


Figure 8. Typical SENS flight test navigation error result from a 1 hour long race track flight (blue), shown in comparison with simulated INS performance results using a tactical grade IMU (HG1930) in purple and a navigation grade IMU (HG9900) in red. Flare Bright's SENS solution outperforms the HG1930 after ~20mins flight time and provides a performance comparable to the gold-standard HG9900 after an hour despite the sensor costing orders of magnitude less.

The key take-home message from Figure 8 is that, for a typical SENS flight, a ~$5 IMU + SENS combination starts outperforming the $10k IMU after ~20 minutes of flight time, referred to as the 'crossover' point. The best flight test results presented in this paper (0.77m/s error growth) indicate a crossover point within 10 minutes into GNSS-free flight, which, if consistent, would open up significant commercial opportunity. For the representative SENS flight shown, the ~$100k HG9900 IMU [13] outperforms SENS throughout the hour-long timeframe. However, as the various error sources contributing to the SENS error growth are further understood and solved, initial, simulation based, projections are that SENS can consistently hit the sub 1m/s error growth range, meaning ~2km - 3km error after an hour - approaching the performance of a $100k IMU using just a ~$5 IMU. In a market where the IMU alone must not cost as much as the rest of the drone itself, and drones have limited payload, the results presented in this paper are very significant.

5. Conclusions

Flight test results of Flare Bright's GNSS-free SENS have been presented and demonstrated the current capability achieved by deploying the software-only solution with a consumer grade IMU on a ~2m fixed wingspan drone. The results from these flights demonstrate a consistent ability to linearise navigation error growth across a variety of flight times, flight paths and platforms.

The results have indicated an average performance of ~2m/s navigation error growth observed, with results across the flight test programme showing a standard deviation of ~ 1.22m/s. This performance was predicted using Flare Bright's Digital Twin simulation capability, highlighting the value of Flare Bright's approach in using virtual environments for capability test/development and performance prediction. Using simulation, Flare Bright is on track to reduce both the average and standard deviation values further.

With this current average flight performance, the paper demonstrates that SENS combined with the ~$5 consumer grade IMU outperforms the equivalent INS only performance using a ~$10k tactical grade IMU (HG1930) within 20mins and has a similar order of magnitude navigation error as a ~$100k navigation grade IMU (HG9900) after an hour. 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. Therefore, as a software only solution, SENS is a route to providing true redundancy and GNSS-jammed navigation capability on a wide range of UAS without adding significant size, weight, power or cost penalties.

6. Patents

Relevant Flare Bright patents include "Fluid flow estimation and navigation" filed on 25 August 2022 and "Digital Twin for an Autonomous Vehicle" filed on 10 Sep 2021.

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