Oppportunistic Autonomous Integrity Monitoring for Enhanced UAV Safety

Joe Khalife, Mahdi Maaref, and Zaher M. Kassas

Abstract—An opportunistic advanced receiver autonomous integrity monitoring (OARAIM) algorithm for unmanned aerial vehicle (UAV) navigation is developed. This algorithm fuses ambient terrestrial signals of opportunity (SOPs) with global navigation satellite system (GNSS) signals to improve the capability of detecting GNSS and SOP measurement faults and provide tight protection level (PL) bounds. A receiver is assumed to make pseudorange measurements on multiple GNSS satellites and terrestrial SOPs. Experimental tests are presented injecting simulated faults into the OARAIM algorithm which successfully detects the faults in GPS satellites and SOPs. Moreover, the OARAIM algorithm and the inclusion of the SOPs reduces the vertical and horizontal PLs by more than 55% and 70%, respectively, compared to only using GNSS measurements.

I. INTRODUCTION

Autonomous unmanned aerial vehicles (UAVs) are predicted to revolutionize a wide range of sectors, such as surveying, farming, filming, construction, transportation, emergency response, infrastructure inspection, and package delivery. As these vehicles approach full-autonomy, the accuracy and integrity of their navigation system become ever more stringent [1]–[4]. While the notion of accuracy is self-explanatory, the notion of integrity is less obvious, but it is of utmost importance in the safety critical application of aviation. Integrity is a criterion to evaluate the reliability and to measure the level of trust in the information produced by a navigation system. A high-integrity navigation system must be able to detect and reject faulty measurements and provide an integrity measure of the confidence in the system performance at any time. Integrity monitoring can be provided through the GNSS navigation messages to indicate satellite anomalies, such as clock errors. However, this type of integrity information is not useful for real-time applications, as it may take on average, about an hour (or less based on recent data), to identify and broadcast the satellite service failure. Thus, alternative frameworks for integrity monitoring have been developed, which can be categorized into: internal and external [5].

External methods (e.g., ground-based augmentation system (GBAS) and satellite-based augmentation system (SBAS)) leverage a network of ground monitoring stations to monitor the transmitted signals [6], while internal methods (e.g., receiver autonomous integrity monitoring (RAIM)) typically use the redundant information within the transmitted navigation signals. RAIM inherently possesses desirable characteristics due to its design flexibility and adaptability [5]. RAIM is a technique primarily based on checking the consistency of redundant measurements. RAIM assesses the availability performance by calculating the protection level (PL) on-the-fly, which is the radius of a circular area centered around the position solution and is guaranteed to contain the true position to within the specifications of RAIM, i.e., with a probability less than or equal to an acceptable integrity risk [7]. By comparing the PL with a pre-defined alert limit (AL), the availability of the navigation system could be determined; specifically, if the PL is less than the AL, the navigation solution is deemed reliable for the pre-defined integrity risk, and unreliable otherwise.

RAIM was initially proposed for GPS-based navigation. Recently, advanced RAIM (ARAIM) algorithms have been developed for multi-constellation navigation systems, which use measurements from different global navigation satellite systems (GNSS) [8]. Nevertheless, relying on GNSS signals alone poses an alarming vulnerability for UAV navigation due to unintentional interference [9], intentional jamming [10], and spoofing [11]. Besides, due to the geometric configuration of GNSS satellites, the vertical error of the GNSS navigation solution is too large for safe UAV navigation in urban environments [12]. To account for GNSS limitations, alternative sensors have been integrated into UAV’s navigation system, and the integrity of these sensors has been the subject of recent studies. Recently, different RAIM schemes incorporating other sensing modalities have been proposed, such as (i) multi-GNSS constellation RAIM (e.g., Galileo-GPS [13], GLONASS-GPS [8], Beidou-GPS [14]) and (ii) GNSS-sensor RAIM (e.g., GPS, inertial measurement units (IMUs), wheel speed encoders, and cameras [15]; GNSS-aided inertial navigation system (INS) [16]; GPS and vision [17]; GNSS and IMU [18]; GNSS, lidar, and IMU [19]; and GPS and lidar [20]).

In addition to sensors, ambient radio signals in the environment, which are not intended for navigation, have been recently considered as a supplement or an alternative to GNSS signals [21]. These signals, termed signals of opportunity (SOPs), can be terrestrial (e.g., cellular signals, digital television signals, AM/FM signals) or space-based (e.g., low Earth orbit (LEO) satellites). SOPs possess desirable characteristics for navigation purposes: (i) ubiquity, (ii) high received power, (iii) large transmission bandwidth, (iv) wide range of transmission frequencies, and (v) geometric diversity. Recent research has demonstrated that cellular SOPs could yield submeter-level-accurate navigation on UAVs [22] and

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This article aims to detect more than one outlier induced into measurements due to LOS signal blockage or multipath. To this end, this article establishes a GNSS-SOP OARAIM framework and calculates the corresponding vertical PL (VPL) and horizontal PL (HPL). Second, a fault-tree and the associated fault probabilities for a combined GNSS-SOP system is developed. Then, the corresponding integrity support message (ISM) parameters for SOPs are discussed (e.g., user range error (URE), user range accuracy (URA), maximum nominal bias, etc.). Third, experimental results with cellular SOPs are presented evaluating the efficacy of the proposed OARAIM framework on a UAV for different fault conditions. A stress test shows that in faulty conditions, the OARAIM algorithm detects the faults in GPS satellites while GPS-only ARAIM fails to detect such faults. Moreover, the OARAIM algorithm reduces the gaps between the VPL and HPL and vertical and horizontal position errors (PEs) by more than 55% and 70%, respectively, compared to only using GNSS measurements.

The rest of this article is organized as follows. Section II presents the proposed OARAIM framework. Section III evaluates the performance of the OARAIM framework numerically and experimentally. Section IV gives concluding remarks.

II. OARAIM FRAMEWORK

This section develops the OARAIM framework to perform integrity monitoring for GNSS-SOP-based navigation. A well-designed integrity monitoring framework provides the UAV with the PLs, i.e., horizontal and vertical regions centered at the UAV’s true position, which are guaranteed to contain the UAV’s estimated position with a certain level of confidence. In this article, a baseline multiple hypothesis solution separation (MHSS) ARAIM, which was introduced in [28], is used to calculate the PLs. In the sequel, ARAIM will refer to MHSS ARAIM, for simplicity. ARAIM is a robust framework for combining navigation signals from different navigation sources with different signal properties, e.g., different URA values and different probabilities of single or multiple simultaneous faults. As such, ARAIM is well-suited for combining SOP signals with GNSS signals to form OARAIM. In addition to providing PLs, OARAIM performs fault detection and exclusion to mitigate the effect of SOP and/or GNSS system faults on the navigation solution. Fig. 2 summarizes the OARAIM GNSS-SOP framework for UAV navigation.

A. Fault tree and fault modes

OARAIM operates on a fault tree. By definition, a fault tree refers to a set of assumptions about the environment in which a RAIM algorithm is applied. The measurements are supposed to be in one out of a set of different branches of the fault tree, to each of which an a priori probability of occurrence is assigned. Therefore, the fault tree can be employed to identify different sources of faults. OARAIM performs multiple statistical tests to detect faults, and then it attempts to exclude the detected faults. The HPL and VPL are subsequently calculated.

OARAIM considers a list of faults that need to be monitored and determines the corresponding prior probabilities that must be assigned to each mode. For simplicity, a GPS-SOP fault

Fig. 1. UAV PLs with ARAIM (GNSS only) and OARAIM (SOP-GNSS).
tree will be discussed. Extension to other GNSS constellations is expected to be straightforward. In [28], a method was presented to determine the faults that need to be monitored and the associated probabilities of faults. Using the same methodology, in this article, a maximum of three simultaneous faults are considered. Also, the probability of a constellation fault (i.e., a fault that affects all transmitters) for both GPS and SOP transmitters are assumed to be sufficiently improbable. This assumption relies on historical record of these signals. GPS records show that there is no evidence of a constellation fault occurrence. In contrast to traditional RAIM frameworks, where pseudorange measurement errors are assumed to have zero-mean, ARAIM accounts for unknown but bounded pseudorange biases denoted by \( \{b_{\text{nom}, \text{GPS}, i}\}_{i=1}^{N_{\text{GPS}}} \). For GPS measurements, these biases bound nominal errors, mainly due to the code correlation peak deformation [31]. The values of the biases are extracted from the ISM and can be limited to 0.75 m [5]. A similar value can be conservatively used for biases in SOP measurements, denoted by \( \{b_{\text{nom}, \text{SOP}, i}\}_{i=1}^{N_{\text{SOP}}} \), as SOP signals are unaffected by atmospheric errors.

A summary of the ORAIM algorithm is given below. The steps below highlight the differences between the ARAIM and ORAIM algorithm. The details of the ARAIM algorithm can be found in [28].

**Step 1:** Compute the pseudorange error covariance matrices denoted \( C_{\text{int}} \) and \( C_{\text{acc}} \), where the former is computed using the URA standard deviations \( \{\sigma_{\text{URA, GPS}, i}\}_{i=1}^{N_{\text{GPS}}} \) and \( \{\sigma_{\text{URA, SOP}, i}\}_{i=1}^{N_{\text{SOP}}} \), and the latter using the URE standard deviations \( \{\sigma_{\text{URE, GPS}, i}\}_{i=1}^{N_{\text{GPS}}} \) and \( \{\sigma_{\text{URE, SOP}, i}\}_{i=1}^{N_{\text{SOP}}} \). Without loss of generality, it is assumed that the combined GPS-SOP measurements are ordered as GPS measurements first then SOP. The diagonal elements of \( C_{\text{int}} \) and \( C_{\text{acc}} \) pertaining to GPS satellites are calculated according to [28], and the ones pertaining to SOPs are given by

\[
C_{\text{int}} \left( N_{\text{GPS}} + i, N_{\text{GPS}} + i \right) = \sigma_{\text{URA, GPS}, i}^2 \tag{2}
\]

\[
C_{\text{acc}} \left( N_{\text{GPS}} + i, N_{\text{GPS}} + i \right) = \sigma_{\text{URE, GPS}, i}^2 \tag{3}
\]

for \( i = 1, \ldots, N_{\text{SOP}} \).

**Step 2:** Compute the all-in-view position solution using weighted least-squares estimation with weight matrix \( C_{\text{int}}^{-1} \).

All available GNSS and SOP measurements are used in this step.

**Step 3:** Determine the fault modes, which are the faults that need to be monitored and their associated probabilities. These modes for the ORAIM algorithm are summarized in the fault tree shown in Fig. 3.

**Step 4:** Evaluate the fault-tolerant positions and associated standard deviations and biases for each fault mode. A fault-tolerant position for a certain mode is computed using all measurements except the measurements of the assumed faulty GNSS satellites or SOPs in that given mode. In particular, this step derives the following parameters for each fault mode:

- The variances of the fault-tolerant position components (East, North, Up) for each fault mode.
- The difference between the fault-tolerant position and the all-in-view position and the variance of this difference.

**B. ORAIM algorithm**

ORAID shares some common inputs and constant parameters used by ARAIM [28]. While some values are independent of the signal type (e.g., total integrity budget, probability of false alarm, etc.), other values are SOP-specific. The ORAIM inputs are tabulated in Table I. In contrast to traditional RAIM frameworks, where pseudorange measurement errors are assumed to have zero-mean, ARAIM accounts for unknown but bounded pseudorange biases denoted by \( \{b_{\text{nom}, \text{GPS}, i}\}_{i=1}^{N_{\text{GPS}}} \). For GPS measurements, these biases bound nominal errors, mainly due to the code correlation peak deformation [31]. The values of the biases are extracted from the ISM and can be limited to 0.75 m [5]. A similar value can be conservatively used for biases in SOP measurements, denoted by \( \{b_{\text{nom}, \text{SOP}, i}\}_{i=1}^{N_{\text{SOP}}} \), as SOP signals are unaffected by atmospheric errors.

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\[
C_{\text{acc}} \left( N_{\text{GPS}} + i, N_{\text{GPS}} + i \right) = \sigma_{\text{URE, GPS}, i}^2 \tag{3}\]

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- The variances of the fault-tolerant position components (East, North, Up) for each fault mode.
- The difference between the fault-tolerant position and the all-in-view position and the variance of this difference.

Fig. 2. Opportunistic navigation framework with OARAIM.
The worst-case impact of the nominal biases $\{b_{\text{nom},\text{GPS},i}\}_{i=1}^{N_{\text{GPS}}}$ and $\{b_{\text{nom},\text{SOP},i}\}_{i=1}^{N_{\text{SOP}}}$ on the position estimate.

Step 5: Perform two sets of tests:

- Solution separation tests:
  - Compute the solution separation test thresholds from the probability of false alarm.
  - Perform the test on all the components of the difference between the fault-tolerant and all-in-view solutions for each fault mode. If any test fails, exclusion must be attempted.

- A chi-squared test:
  - A chi-squared test is performed on the measurement residuals for the all-in-view solution with weight matrix $C_{\text{acc}}$ calculated in Step 1.
  - The threshold is computed using the inverse chi-squared cumulative density function (cdf) and a pre-defined probability of false alarm.
  - If the chi-squared test fails, the PLs cannot be considered valid and exclusion cannot be attempted. If this test fails while none of the solution separation tests fail, then the fault is most likely outside the threat model. The chi-square test is a sanity check for that purpose.

Step 6: Calculate the PLs if all of the solution separation tests and the chi-squared test pass and formulate the vertical positioning performance criteria:

- Criterion 1: $95\%$ accuracy parameter, which is the achievable positioning accuracy in the vertical domain $95\%$ of the time. According to the Localizer Performance with Vertical guidance (LPV)-200 standard, the $95\%$ accuracy must be limited to $4$ m.

- Criterion 2: $10^{-7}$ fault-free position error bound, which is the achievable positioning accuracy in the vertical domain $99.99999\%$ of the fault-free time. According to the LPV-200 standard, the $10^{-7}$ fault-free position error bound must be limited to $10$ m.

- Criterion 3: Effective monitor threshold (EMT), which is a parameter that takes into account the faults with a priori probability. According to the LPV-200 standard, EMT must be limited to $15$ m.

If the chi-squared test passes but any of the solution separation tests fail, the following steps are performed instead.

Step 7: Exclude the faults by first determining the candidate subset to exclude. This is achieved by performing a search over
all possible subsets to find the subset that yields the highest discrepancy between the fault-tolerant and all-in-view solution. Once the best candidate subset is determined, an exclusion test is performed to account for the wrong exclusion probability.

**Step 8:** Compute the PLs after exclusion. This step is similar to **Step 6** except that it accounts for the wrong exclusion probability.

**Step 9:** Compute the 95% accuracy criterion after exclusion to account for fault modes.

**Remark:** Note that the above used LPV-200 requirements, which were developed for aircraft operation, since no formal integrity requirements established for small UAs as of yet. As stakeholders develop such requirements for UAs, the parameters in the OARAIM algorithm can be adjusted accordingly.

Fig. 4 summarizes the proposed OARAIM algorithm.

<table>
<thead>
<tr>
<th>Input</th>
<th>Description</th>
<th>Obtained from</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\sigma_{URA,GPS})<em>{i=1}^{N</em>{GPS}}$</td>
<td>Standard deviation of GPS user range accuracy</td>
<td>ISM</td>
</tr>
<tr>
<td>$(\sigma_{UAR,SOP})<em>{i=1}^{N</em>{SOP}}$</td>
<td>Standard deviation of SOP user range accuracy</td>
<td>ISM</td>
</tr>
<tr>
<td>$(\sigma_{URE,GPS})<em>{i=1}^{N</em>{GPS}}$</td>
<td>Standard deviation of the GPS user range error</td>
<td>ISM</td>
</tr>
<tr>
<td>$(\sigma_{URE,SOP})<em>{i=1}^{N</em>{SOP}}$</td>
<td>Standard deviation of the SOP user range error</td>
<td>ISM</td>
</tr>
<tr>
<td>$(\mu_{nom,GPS})<em>{i=1}^{N</em>{GPS}}$</td>
<td>Maximum bias for a GPS measurement</td>
<td>ISM</td>
</tr>
<tr>
<td>$(\mu_{nom,SOP})<em>{i=1}^{N</em>{SOP}}$</td>
<td>Maximum bias for a SOP measurement</td>
<td>Similar to the GPS maximum bias</td>
</tr>
<tr>
<td>$(\alpha_{GPS})<em>{i=1}^{N</em>{GPS}}$</td>
<td>Probability of a single GPS fault</td>
<td>Experimental campaign. Proposed value is $10^{-5}$</td>
</tr>
<tr>
<td>$(\alpha_{SOP})<em>{i=1}^{N</em>{SOP}}$</td>
<td>Probability of a single SOP fault</td>
<td>Historical records. Proposed value is $10^{-4}$</td>
</tr>
<tr>
<td>$P_{const,GPS}$</td>
<td>Probability of GPS constellation fault</td>
<td>Historical records. Currently used value is 0</td>
</tr>
<tr>
<td>$P_{const,SOP}$</td>
<td>Probability of SOP constellation fault</td>
<td>Experimental campaign. Proposed value is 0</td>
</tr>
</tbody>
</table>

### III. PERFORMANCE EVALUATION

This section evaluates the performance of the OARAIM framework numerically and experimentally. The OARAIM algorithm was implemented using the MATLAB Algorithm Availability Simulation Tool (MAAST) [29], [32].

#### A. Simulation Results

In order to study the performance of the OARAIM algorithm under fault-free and faulty conditions, a simulation was performed with 2 SOPs. For this test, GPS signals were obtained from a stationary receiver at the Madrid Deep Space Communications Complex (MDSCC). The elevation and azimuth angles of the GPS satellite constellation above the receiver over a 24-hour period was computed using GPS ephemeris files collected at the MDSCC. The GPS observations were extracted from the recorded Receiver Independent Exchange Format (RINEX) file. Then, the SOP signals were simulated using a high-fidelity SOP simulator that has been used in previous research [24]. The SOP and receiver’s clock qualities were modeled as typical oven-controlled crystal oscillator (OCXO) and temperature-compensated crystal oscillator (TCXO), respectively. To overcome the unknown nature of the SOP transmitter’s clock bias and its drift, which in GNSS-based navigation are known through the navigation message, a reference receiver, referred to as the base, is assumed to be present in the UAV’s environment to provide differential corrections. Moreover, it is assumed that the base has direct line-of-sight (LOS) to all of the cellular towers to eliminate the possibility of common errors. The impact of using a base receiver on an SOP-based integrity monitoring framework has been fully investigated in reference [24], where a base receiver was employed to estimate the SOP clock biases through a
Kalman filter. Considering that the base receiver could be deployed on top of a building, it can be assumed that it has access to unobstructed GNSS signals from which it can estimate its own clock bias. Hence, for the purpose of this study, it is assumed that the base has complete knowledge of its position and its clock bias and that it does not introduce a non-zero mean common mode error in the UAV’s differential measurements. Once the measurements are corrected, a common clock bias term remains to be estimated, and is added to the set of constellation clock biases to be estimated.

In the first scenario, both SOPs were fault-free. In the second scenario, a fault of a magnitude of 30 m was injected into the second SOP measurement. To illustrate the accuracy and integrity performances simultaneously, a so-called Stanford diagram was plotted in Fig. 5, where the PE, PL, and AL are shown for four scenarios: GPS-only (black dots), GPS-SOP in fault-free operation (blue dots), GPS-SOP without OARAIM fault exclusion (red dots), and GPS-SOP with OARAIM fault exclusion (blue dots). The AL was set to 30 m.

Note that except for the red points, the PLs in Fig. 5 are calculated only after tests have passed, or after exclusion in the case where faults are detected. However, similar to [7], the PLs before exclusion (red) are shown in the Stanford plot for a comparative analysis. The following may be concluded from Fig. 5.

1. First, by comparing the blue and black dots, it can be seen that adding SOPs eliminates system unavailability. The AL was set to 30 m.
2. Second, injecting the fault into an SOP measurement caused a misleading operation (red dots); however, the OARAIM algorithm rejected the faulty measurement to achieve nominal operation (green dots). Third, by comparing the red and green dots, it can be seen that as expected, fault exclusion results in reducing the PE. However, one can spot green and blue dots in the misleading operation region. With only two SOPs, the integrity system will heavily couple the GPS and SOP “constellations” since there are not enough SOPs to compute an SOP-only position solution. This could explain the occasional green or blue point in the misleading operation region. However, one can see that the PL is reduced on average when SOPs are used with GPS for integrity, as shown by the lowered green and blue cloud points compared to the GPS’s black point cloud.

Fig. 5. The Stanford diagram demonstrating the horizontal accuracy and integrity performances simultaneously.

B. Experimental Results

In order to evaluate the performance of the proposed OARAIM framework in a real-world scenario, a DJI Matrice 600 UAV was equipped with a dual-channel National Instrument (NI) universal software radio peripheral (USRP)-2955 to sample cellular long-term evolution (LTE) SOPs at four LTE carrier frequencies: 739, 1955, 2125, and 2145 MHz. These frequencies are allocated for the U.S. cellular providers AT&T, T-Mobile, and Verizon. The ground-truth reference for the UAV’s trajectory was taken from a Septentrio AsteRx-i V integrated GNSS-IMU system, which is capable of producing a submeter-level accurate real-time kinematic (RTK) navigation solution. Fig. 6 shows the experimental hardware and software setup and Fig. 7 shows the experimental environment.

The UAV flew for 4 minutes, while collecting LTE signals from 11 LTE SOP transmitters in the environment. The stored LTE signals were then processed by the LTE module of the Multichannel Adaptive Transceiver Information eXtractor (MATRIX) SDR to produce LTE SOP pseudoranges, which were then fused with GPS pseudorange measurements obtained from the Septentrio receiver to produce the navigation solution along with the corresponding OARAIM integrity measures, as shown in Fig. 7.

Two scenarios were considered to evaluate the impact of SOP measurements on navigation and safety: (i) fault-free conditions and (ii) faulty conditions with faults in two GPS satellites. The faults were injected artificially as a stress...
A very preliminary study found in [12] that the measurement error for UA V flights is around 0.75 m at high altitudes, in a semi-urban environment. While the UAV is flown in a similar environment in this paper, this value of $\sigma_{UR,A,SOP,i}$ was inflated by 25% to be more conservative. As such, the ARAIM and OARAIM algorithms were implemented with $\sigma_{UR,A,SOP,i} = 1.1 \text{ m}$, $\sigma_{UR,GPS,i} = 0.75 \text{ m}$, $\sigma_{UR,A,SOP,i} = 1.4 \text{ m}$, $\{b_{\text{nom},GPS,i}\}_{i=1}^{N_{GPS}} = 0.5 \text{ m}$, and $\{b_{\text{nom},SOP,i}\}_{i=1}^{N_{SOP}} = 0.75 \text{ m}$, for all $i$. Moreover, it was found in [12] that the measurement error for UAV flights is less than 5.42 m. Using this standard deviation as a definition of a fault at high altitude in a semi-urban environment yields an SOP fault probability of about $10^{-4}$ (corresponding to $3.89\sigma_{UR,A,SOP,i}$). Therefore, the prior satellite fault probabilities were set to $10^{-5}$ and the prior SOP fault probabilities were set to $10^{-4}$, with zero probability for constellation faults. The $\sigma_{UR,A,SOP,i}$ and $\sigma_{UR,A,SOP,i}$ values are relatively low since cellular signals received by UAVs do not suffer from severe multipath by virtue of the favorable channel between base stations and UAVs. In fact, a recent study of UAV connectivity to the cellular network demonstrated that the received cellular signal power on low-altitude UAVs (30 m to 120 m) are stronger than the receiver power on ground-based receivers, despite the downwards-tilted cellular antennas [33]. The study attributes these findings to the fact that “free space propagation conditions at altitude more than make up for antenna gain reductions.” It is important to note that the reliability of cellular SOP has not been fully characterized yet. As such, a $10^{-4}$ fault probability could be either conservative or optimistic. However, in the case of the latter, it has been shown in [34] that OARAIM would still yield improvement over ARAIM for high and unlikely SOP fault probabilities of $10^{-2}$.

One important integrity functionality studied in these experiments is fault detection. Fig. 8 shows the chi-squared test results for the GPS-only and GPS-SOP systems in fault-free and faulty conditions. The main takeaway from Fig. 8 is that although the test threshold increases by adding SOP measurements (a straightforward property of chi-squared-distributed random variables), the test statistic itself becomes more sensitive to faults. This also applies to the solution separation tests, which are not shown here for brevity. No faults were detected by the GPS-only ARAIM system in the fault regime, whereas the GPS-SOP OARAIM system detected such faults. It is worth pointing out that while Fig. 8 studied the chi-squared test results, studying the solution separation test results would yield a large number of cases, which is
deferred to future work.

![Graph](image_url)

**Fig. 8.** Time history of the chi-squared test statistic for GPS-only and GPS-SOP with their respective test thresholds. The test statistic for each system are shown in fault-free and faulty conditions. The shaded area represents faulty conditions.

Next, the gap between the HPL and the horizontal position error (HPE), and the gap between the VPL and vertical position error (VPE) were studied. The gap between PLs and PEs is an indicator of the tightness of the PLs. The gaps are calculated according to $\Delta V \triangleq VPL - VPE$ and $\Delta H \triangleq HPL - HPE$. The root mean-squared error (RMSE) of $\Delta V$ and $\Delta H$ were computed for both GPS-only and GPS-SOP and in fault-free and faulty conditions. The results are tabulated in Table II and Fig. 9.

**TABLE II**

<table>
<thead>
<tr>
<th>Approach</th>
<th>Condition</th>
<th>$\Delta H$ RMSE</th>
<th>$\Delta V$ RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPS-only ARAIM</td>
<td>Fault-free</td>
<td>26.9 m</td>
<td>24.7 m</td>
</tr>
<tr>
<td>GPS-SOP OARAIM</td>
<td>Fault-free</td>
<td>7.5 m</td>
<td>11.0 m</td>
</tr>
<tr>
<td>GPS-only ARAIM</td>
<td>Faulty</td>
<td>25.3 m</td>
<td>24.8 m</td>
</tr>
<tr>
<td>GPS-SOP OARAIM</td>
<td>Faulty</td>
<td>7.6 m</td>
<td>11.4 m</td>
</tr>
</tbody>
</table>

The following can be concluded from Table II and Fig. 9. First, $\Delta H$ and $\Delta V$ are reduced significantly when SOP measurements are added, with more than 70% reduction in the $\Delta H$ RMSE and more than 55% in the $\Delta V$ RMSE. Fig. 9 shows that while the PLs were significantly reduced, the PEs slightly reduced as well. This implies that adding SOP measurements significantly tighten the PLs towards the PEs without the PEs exceeding the PL. This is a desirable behavior as it moves the system more to the left of the “Nominal operation” region shown in Fig. 5. Second, the change in the $\Delta H$ RMSE between fault-free and faulty conditions for GPS-only is much greater than the change for the GPS-SOP, i.e., around 6% compared to 1.3%, respectively. The reduction in the GPS-only $\Delta H$ RMSE is due to the HPEs getting larger because of the undetected faults while the HPL remained unchanged. This undesirable behavior brings the system closer to the “Misleading operation” region of Fig. 5. In the case of GPS-SOP, the faults are detected and excluded properly, maintaining low $\Delta H$ and $\Delta V$ RMSEs in the presence of faults. It is important to note that in this particular experiment, the VPL is lower than the HPL in the case of GPS-only, as shown in Fig. 9. This may be due to the fact the probability of hazardous misleading information (PHMI) for the VPL is about 100 times the PHMI for the HPL when using standard ARAIM parameters from the GPS ISM, as shown in Table I. However, the ARAIM system does not necessarily need to detect the faults with high probability. In this study, both the GPS-SOP OARAIM and the GPS-only ARAIM algorithms were set up with standard ISM values shown in Table I for a comparative analysis. Tuning and designing the OARAIM and ARAIM parameters for optimal performance is left for future work.

**Remark:** While the presented simulation and experiment results look promising, they are not enough to generalize the conclusions. They provide an insight into the potential of SOPs in improving integrity monitoring. Extensive simulations and experiments are needed to generalize the results obtained in this paper and are left as future work.

**IV. CONCLUSION**

To improve the availability of the integrity monitoring system, the capability to detect faults must be improved and PLs must remain small. This article showed that by incorporating SOPs, the fault detection probability is increased and PLs can be made smaller than the ones from current GNSS constellations. To this end, the article presented an OARAIM framework for enhanced UAV safety. OARAIM enables safe UAV navigation by fusing GNSS signals with ambient SOPs, producing tight PLs, while identifying and excluding faults, if present. A fault tree was constructed for GPS-SOP-based navigation and the OARAIM algorithm was presented. Simulation results were presented demonstrating that adding SOPs eliminates system unavailability of the integrity system. Experimental results were presented showing that in faulty conditions, the OARAIM algorithm detects the faults in GPS satellites while GPS-only ARAIM failed to detect such faults. Moreover, the OARAIM algorithm reduces
the gaps between vertical and horizontal PLs and PEIs by more than 55% and 70%, respectively, compared to only using GNSS measurements. The PL reduction in OARAIM translates to higher availability of the integrity monitoring system, allowing the UAV navigation system to meet more stringent integrity standards than ARAIM with GNSS only.

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REFERENCES

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