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A Solution to GNSS-Denied Navigation for Aeronautics—Combining GNSS-Denied Navigation Means and Collaborative Navigation †

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Abstract

This paper presents how the combination of Vision-based Navigation (VBN), Terrain Referenced Navigation (TRN) and Star Navigation complement each other to tackle the challenge of GNSS-denied navigation for aeronautics covering a wide range of environmental and operational conditions. Moreover, Collaborative Navigation contributes to GNSS-denied navigation capability by distributing the position information within the group of collaborating platforms in a stochastically optimal way using an Extended Kalman Filter.

Keywords: GNSS-denied navigation; Collaborative Navigation; Vision-based Navigation; Terrain Referenced Navigation; Celestial Navigation; Multi-Sensor Fusion; aeronautical Navigation; Extended Kalman Filter

1. Introduction

As of today, there is no GNSS-denied means that are a 1:1 replacement for GNSS. On the other hand, the incidents of GNSS-denial are increasing [1], potentially compromising the safety and mission success rate of military aircraft.

This paper presents an approach for which several GNSS-denied navigation means, as well as Collaborative Navigation, are combined to overcome GNSS-denial in wide range of environmental and operational conditions. Especially, Collaborative Navigation exposes great potential but requires a change in mindset as relative accuracy rather than absolute accuracy is of interest.

2. GNSS-Denied Navigation Means

All onboard autonomous absolute GNSS-denied navigation means have in common that they correlate sensor data with environmental features. The availability and performance largely depend on the existence of environmental features and capability to sense these environmental features. For example, a camera of a Vision-based Navigation (VBN) system may not "see" environmental features (although physically present) in foggy conditions.

Therefore, complementary GNSS-denied navigation means need to be combined to cover the wide range of environmental conditions. Figure 1 depicts the approach of Airbus Defence and Space by combining VBN (light blue), Terrain-Referenced Navigation (TRN) (light red) and Star Navigation (StarNav) (yellow doted lines). The environmental and operational conditions are divided by the availability of landmarks, visibility conditions

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(e.g., obstruction by clouds) and altitude. VBN is operational if visibility to landmarks is given. StarNav is complementary to VBN as no landmarks are required, but visibility to the stars is mandatory. Last but not least, TRN completes the GNSS-denied navigation system for operation in low-visibility conditions and for Low-Level Flight (LLF) operations.

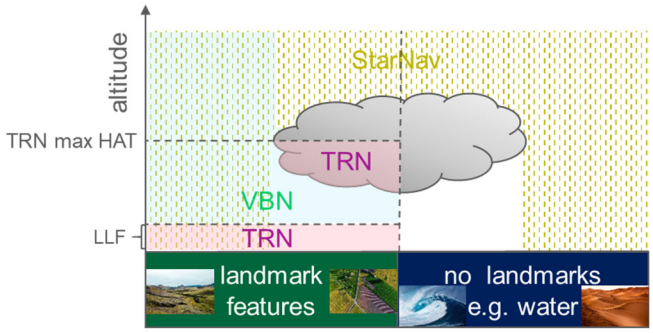


Figure 1. Complementary GNSS-denied navigation means; VBN in light blue, TRN in light red and StarNav in yellow dotted lines [2–5].

Each of the GNSS-denied navigation methods has its own technical challenges, which may lay in one of the three essential technical components that are common for any onboard-autonomous absolute GNSS-denied navigation method: Firstly, the sensor system which senses the features. Secondly, the subsequent sensor data processing, which extracts useful navigation from the sensor data by matching the sensed data against, third, a geo-referenced database for absolute localization. Last but not least, integration and certification may also pose a challenge.

In the following sub-chapters, the working principles of VBN, StarNav and TRN are introduced, their environmental and operational coverage are discussed, and finally, their challenges are addressed.

2.1. Vision-Based Navigation (VBN)

The deployed VBN system uses Structure from Motion (SfM) to estimate the pose (position and attitude) of the aircraft by tracking visual features across multiple frames. The main steps of the processing pipeline are shown in Figure 2 and are discussed below in connection with the key parameters affecting its performance.

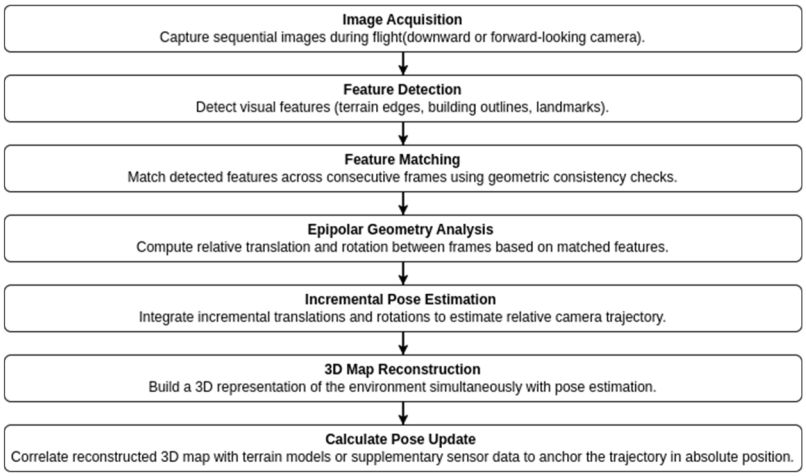


Figure 2. Structure from Motion (SfM) Processing Pipeline for VBN.

The pipeline begins with the image acquisition. The image resolution, the field of view (FoV), and the flight altitude determine the ground sampling distance (GSD). A smaller

GSD provides higher spatial detail which supports more accurate feature localization, and hence, position estimation. A wide FoV increases the terrain context by exposing more landmarks per frame but also causes an increase in GSD. Moreover, the modular transfer function (MTF) of the camera needs to be taken into account as it reduces the effective GSD and is determined by the quality of the optics and atmospheric transmission. Motion blur—which increases linearly with velocity and angular rate and decreases indirectly proportionally with altitude—degrades feature localization accuracy, too. In order to maintain localization accuracy, exposure time shall be sufficiently short to not exceed the tolerable motion blur threshold. Furthermore, to support night operations or degraded visual conditions, infrared cameras are used, as they do not require an external light source such as the sun or the moon.

In the feature detection step, salient points such as corners, edges, or blobs are extracted from each image. The reliability of this step depends on the image quality explained above, the scene contrast and the texture. However, scenes with low contrast or uniform texture (e.g., snow, desert) reduce the number of usable features and expose a challenge for detection.

Once features are detected, the feature matching establishes correspondences across frames. The robustness of this step is influenced by the motion of the aircraft and the texture. To compensate for rapid motion, IMU data are used to predict the expected movement of features in the image plane. Additionally, repetitive or moving patterns in the environment (e.g., crop fields) introduce further ambiguity in matching.

In the pose estimation stage, the relative motion of the aircraft is computed from matched features using epipolar geometry. This yields frame-to-frame rotations and translation directions, but the result remains up to scale. These transformations are integrated to reconstruct the camera trajectory and a 3D map of the environment. The accuracy of the depth estimation depends on the feature parallax: a low-altitude flight yields larger parallax and better depth precision, while a high-altitude flight produces flatter reconstructions. An example of a 3D reconstruction result alongside the corresponding electro-optical camera image is provided in Figure 3.

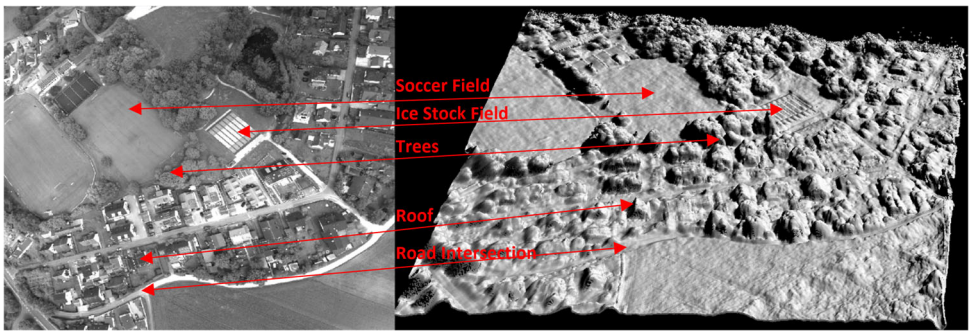


Figure 3. Electro-optical camera image (**left**), 3D reconstruction result (**right**).

To convert the relative trajectory into an absolute position, the scale ambiguity must be resolved. This is achieved by matching the 3D reconstruction or the pose estimates with a Digital Surface Model (DSM). The quality of this co-registration and the resolution of the DSM affect the localization accuracy. Moreover, any geo-registration error of the DSM directly propagates into the final navigation solution.

The primary strength of an SfM-based VBN lies in its ability to deliver highly accurate absolute navigation by exploiting the rich spatial information contained in the image sequences. Additionally, the approach of SfM is robust compared to the approach of direct visual co-registration which compares in-flight images with a satellite image database which can significantly differ in terms of scenes such as vegetation and lighting conditions.

However, the performance as of any VBN system is inherently constrained by factors such as scene visibility, feature richness, and computational demands. Furthermore, certification and integrity considerations pose a challenge due to the difficulty of verifying a VBN system across the infinite set of scenes and lighting conditions, as well as formally proving the correctness of the reference database.

2.2. Star Navigation

Star Navigation has guided travellers since antiquity based on sextants. Modern star trackers combine digital optics, the star catalogue, and on-board processing to deliver attitude rotation quaternions in the ECI frame with arc-second accuracy [6]. Daylight operation adds an additional layer of complexity requiring narrow-band filters, advanced image processing, and a limited field-of-view to suppress sky radiance [7,8].

A star tracker begins by forming a deliberately defocused image of the stars such that each star (that is a point source) illuminates several pixels. A weighted centroid algorithm then yields the line-of-sight vector towards the star with sub-pixel accuracy [6]. Subsequently, at least three candidate vectors (forming a star constellation) are matched with the star catalogue which allows us to conclude the aircraft attitude w.r.t. the ECI frame (called inertial attitude in the following).

However, the inertial attitude does not contain explicit position information because the distance to the stars is practically infinite, and hence, any position in the Earth's proximity does not cause any parallax of stars which prohibits multiangulation. Moreover, latitude and longitude cannot uniquely be determined from the inertial attitude as there are infinite combinations of position, local attitude and time, resulting in the same inertial attitude equivalent to an underdetermined LSE. Figure 4 illustrates an example of two combinations of position and local attitude which yield the same inertial attitude.

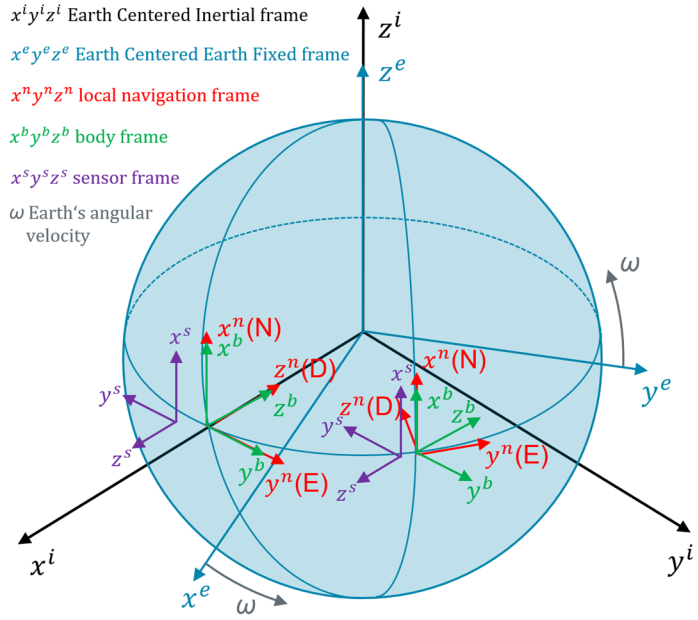


Figure 4. An example of two different aircraft positions and attitudes w.r.t. the local navigation frame leading to the same inertial attitude.

Nonetheless, fusing the inertial attitude with IMU data can effectively reduce the position drift from a cubic error growth to a square-root error growth (linear short-term approximation and neglecting the error contribution of the accelerometers) as explained in the following:

A strapdown algorithm integrates gyroscope rates to obtain the local attitude. Accelerometer outputs are projected with that attitude into the navigation frame and integrated twice to determine the velocity and position. Therefore, a constant gyro bias b results in a time t linearly growing tilt error $\theta(t) = bt$. In turn, the tilt error causes a misaligned projection of the gravity vector, which produces a horizontal acceleration error $g\theta(t) = gbt$. Integrating the acceleration twice yields a position drift which is proportional to t^3. Thanks to the star tracker updates, the constant gyroscope bias is fully observable such that only the white noise of the gyroscope measurements remains. During the period Δt between two consecutive star tracker updates, the white noise is integrated causing a random walk which leads to a mis-projection of the gravity vector and generates a position drift of $C\Delta t^{5/2}$, where C is a constant. After $N = t/\Delta t$ independent updates, these offsets add up in a root-sum-square manner such that $\sigma_{pos} = C\Delta t^{5/2}\sqrt{N} = C\Delta t^2\sqrt{t}$, and hence, the overall position error grows with the square root of time t rather than cubically [9].

The main challenge of a daytime star tracker is the unfavourable SNR of the star light compared to background noise, namely the Rayleigh scattering causing the sky to appear blue. A useful SNR is only achieved by long integration times of the imaging detector of the star tracker because the signal of the uncorrelated background noise increases only with the square root of time while the useful correlated star light increases linearly. A smaller field of view (FoV) of the star tracker is also beneficial for the SNR allowing it to detect fainter stars. The drawback of a small FoV is that fewer stars are contained in the FoV and stars pass the FoV faster, reducing the permissible aircraft turn rates. Last but not least, the altitude impacts the SNR—the higher the altitude, the less atmosphere is in-between the star tracker and the stars, which causes unwanted Rayleigh scattering. The parameters FoV, integration time, permissible aircraft turn rate, and altitude need to be taken into account during the trade-off.

The integration needs to be carefully done, especially in terms of misalignment between star tracker and INS/IMU to exploit the arc-second accuracy of a star tracker. A small calculation example shows that a misalignment of 1 arc-second corresponds to a 31 m horizontal position error, assuming that the aircraft local attitude is perfectly known. Therefore, star tracker and INS/IMU shall ideally share the same mechanical mount to minimize dynamic misalignment due to mechanical or thermal stress. The static misalignment component can be calibrated by having accurate position information.

Mastering the challenges is rewarded with a world-wide operation capability and a system which is inherently spoofing-resistant and hard to jam.

2.3. Terrain Referenced Navigation (TRN)

TRN supplements the GNSS-denied navigation system with all-weather, especially low visibility, operation capabilities.

A radar altimeter is used for TRN to sample the shortest slant range to the terrain (see slant range measurement and slant range profile in Figure 5). Having the slant range measurement, flight path and the baro-inertial altitude, the terrain elevation can be approximately determined (see altitude "minus" slant range profile of Figure 5) and subsequently matched with a digital surface model (DSM) to obtain the aircraft position.

There are two major principles to estimate the aircraft position:

Firstly, the gradient-based method compares the slant range gradient as determined from two consecutive measurements and tries to match it with the gradient computed from the digital surface model (DSM). While this approach is computationally inexpensive, the robust suffers as the ambiguity of the gradient may lead to instability (erroneous filter update).

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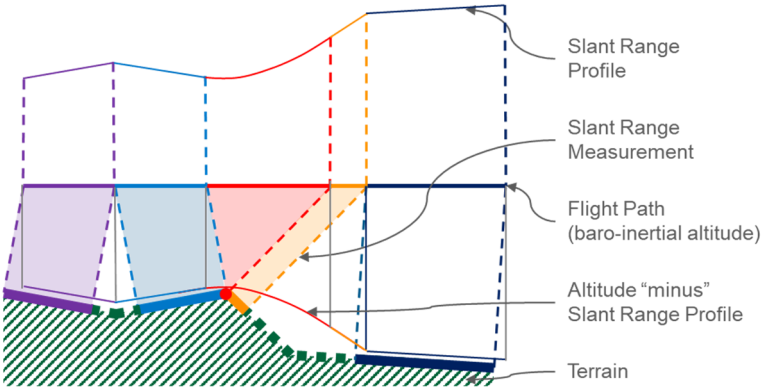


Figure 5. Shortest slant range and terrain topography.

The approach chosen in this paper uses a series of slant range measurements, called "slant range profile". Moreover, the associated position estimates are recorded, forming the flight path. The first step of the matching process is to determine the search area based on the position uncertainty. The search window is chosen conservatively such that the true position is contained with high probability (e.g., 99.9% percentile).

Secondly, the flight path is virtually shifted in the DSM within the search window to obtain a hypothetic slant range profile The matching process minimizes the Mean Absolute Difference (MAD) between the measured and the hypothetic slant range profile until convergence is reached. The position hypothesis with the minimum MAD is output by the TRN algorithm. The residuum of the matching process as well as the roughness of the terrain are used to estimate the position uncertainty of TRN in order to correctly weigh the TRN solution in the sensor fusion. The greater the roughness/significance of the terrain, the better the accuracy of TRN.

The main advantage of this approach is its robustness due to the uniqueness of the slant range profile which comes with the cost of increased computational load.

Independent of the approach, a radar altimeter with a specialized firmware is required to report the shortest distance rather than the strongest reflection as a typical radar altimeter does. The operational height above terrain of TRN is limited by the maximum operating range of the radar altimeter which is typically around 5000 ft. TRN is well-suited for Low-Level Flight at high speeds compared to VBN because it is not affected by motion blur.

3. Collaborative Navigation

In the era of systems of systems, Collaborative Navigation becomes part of the solution for GNSS-denied navigation, although it does not directly contribute to it.

Figure 6 depicts the architecture of Collaborative Navigation. The Sensor Suite contains the navigation sensors of a traditional aircraft such as the Inertial Navigation System (INS), Global Navigation Satellite System (GNSS) as well as GNSS-denied navigation means. Moreover, the Sensor Suite is equipped with relative navigation sensors such as camera or LiDAR and a datalink. The relative navigation sensor is required to provide information about the relative position/velocity/attitude of the other swarm members. The datalink is not a sensor itself, but it is required to exchange navigation information between the swarm members [10].

The Main Filter is an Extended Kalman Filter (EKF) which provides the absolute state estimation (position, velocity and attitude) and the according covariance of the own platform. The Main Filter fuses INS, the absolute navigation means of the own platform and the relative navigation information of the entire swarm via the Consistent INS Drift Algorithm [10].

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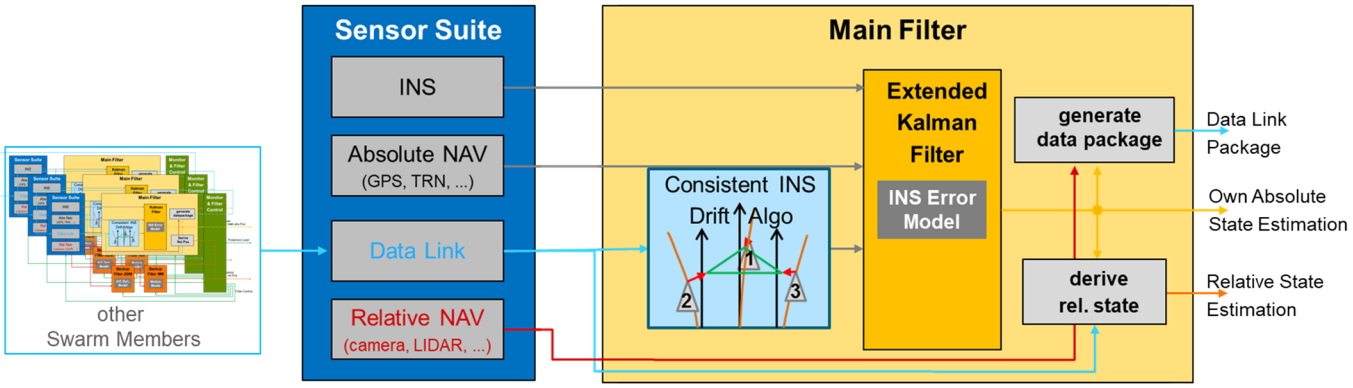


Figure 6. Architecture of Collaborative Navigation.

The Consistent INS Drift Algorithm distributes the (absolute) state innovation between swarm members to reassemble the relative geometry as measured by the relative sensor(s) and to simultaneously minimize the absolute estimation error [10].

With this approach, the absolute-state estimations of the swarm members have a high relative accuracy despite GNSS-denied conditions. The relative accuracy is essential that accurate absolute navigation information of swarm members is spread within the formation.

Figure 7 showcases this for a formation of three aircrafts for which aircraft "1" has an operational VBN system while aircrafts "2" and "3" have neither GNSS nor GNSS-denied navigation capabilities. Nonetheless, aircraft "2" and "3" show an absolute position accuracy comparable to aircraft "1".

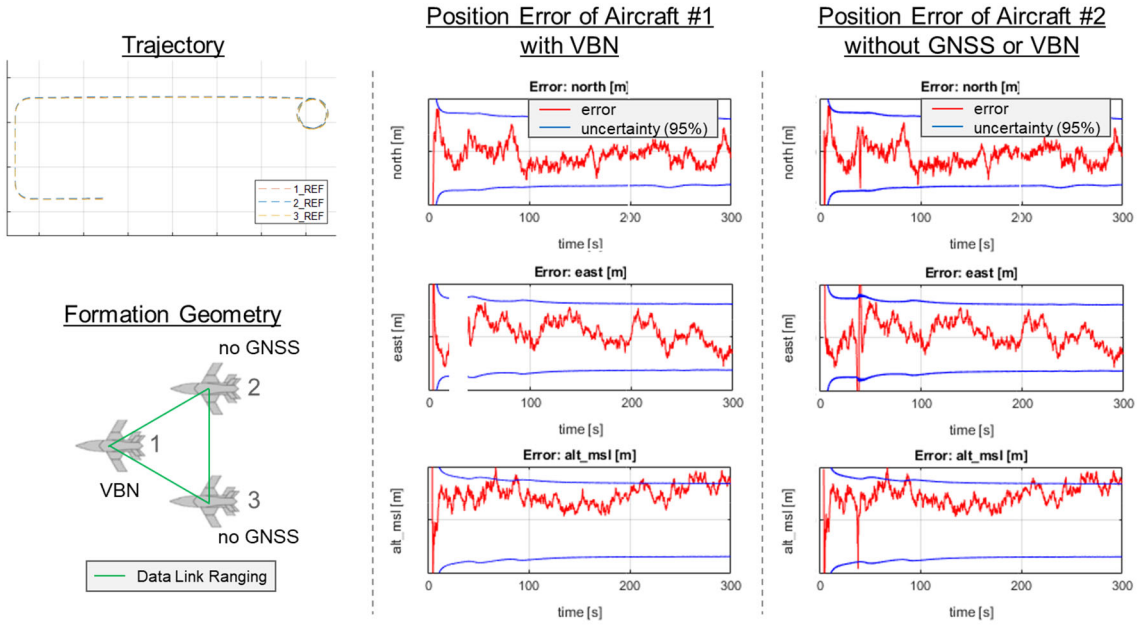


Figure 7. Collaborative Navigation—spreading accurate absolute within swarm.

This allows for a heterogenous swarm whereas different assets contribute by different GNSS-denied navigation capabilities. However, Collaborative Navigation comes with the drawback that it depends on a data link to exchange the required navigation information.

4. Conclusions

The combination of Vision-based Navigation (VBN), Star Navigation (StarNav) and Terrain Referenced Navigation (TRN) can substitute GNSS to a great extent. VBN is the

cornerstone due to its high accuracy but is susceptible to low-visibility conditions and requires ground features. TRN complements VBN with all-weather operation capabilities but is limited by the maximum operating altitude of the radar altimeter and the need for terrain. On the other hand, StarNav is the only navigation mean of the proposed GNSS-denied navigation means which works over feature-less terrain. However, StarNav provides only inertial attitude ("attitude w.r.t. the stars") and does not provide an absolute position. Therefore, the position error is not fully observable in the navigation filter leading to a position drift which grows only with $\sqrt{t}$ instead of t^3.

A good candidate to further improve navigation performance, especially over feature-less terrain, is Signals of Opportunities (SoOP) based on LEO satellites. However, SoOP contradicts the on-board autonomous working principle of the GNSS-denied navigation system as it relies on external infrastructure (satellites) which may be subject to shut-down or unavailability of accurate ephemeris data which may jeopardize availability and/or integrity.

Last but not least, Collaborative Navigation can contribute to the GNSS-denied navigation capabilities. Firstly, swarm members with a poor absolute-position accuracy benefit from those with a high-position accuracy. This is due to the relative accuracy which is achieved for instance through data link ranging which allows to distribute absolute navigation information within the formation in a weighted least squares manner. Finally, despite the unavailability of GNSS as well as GNSS-denied navigation means the relative navigation accuracy is maintained. The relative accuracy is sufficient to allow for the formation flight and similar missions tasks but requires rethinking the classical absolute navigation approach.

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Abbreviations

DSM	Digital Surface Model
ECI	Earth-Centred Inertial
FoV	Field of View
GmbH	Gesellschaft mit beschränkter Haftung

GNSS	Global Navigation Satellite System
GSD	Ground Sampling Distance
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
IRS	Interface Requirements Specification
LEO	Low Earth Orbit
LiDAR	Light Detection And Ranging
LLF	Low-Level Flight
LSE	Linear System of Equations
MAD	Magnetic Anomaly Detector
MDF	Modular Transfer Function
SfN	Structure from Motion
SNR	Signal to Noise Ratio
SoOP	Signals of Opportunities
StarNav	Star Navigation/Celestial Navigation
TRN	Terrain Referenced Navigation
VBN	Vision-based Navigation

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