Autonomous Angles-Only Navigation for Spacecraft Swarms around Planetary Bodies

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Abstract—This paper presents and demonstrates an algorithmic framework for autonomous navigation of spacecraft swarms around planetary bodies, using angles-only measurements from onboard cameras. Angles-only methods are compelling as they reduce reliance on external measurement sources. However, prior demonstrations have faced significant limitations, including 1) the inability to treat more than one observer and target in a swarm, 2) lack of autonomy and reliance on external state information, and 3) treatment of only Earth-orbit scenarios. The new Absolute and Relative Trajectory Measurement System (ARTMS) overcomes these challenges, and consists of three core modules: Image Processing, which identifies and computes bearing angles of targets in camera images; Batch Orbit Determination, which computes a swarm state initialization from IMP measurements; and Sequential Orbit Determination, which uses an unscented Kalman filter to navigate after initialization. Together, these algorithms leverage distributed measurements from multiple swarm observers to achieve the necessary autonomy, robustness and distribution for deep space navigation. The theoretical performance of ARTMS is investigated through a quantitative observability analysis of multiobserver angles-only navigation in Mars orbit. For swarms of ≥3 spacecraft and ≥2 observers, the complete swarm state is observable. After two orbits, the absolute orbit is estimated to within 1km, target ranges are estimated to 0.5%, and other relative state components are estimated to 0.02% of target range. Clock drifts are estimated to within 0.05s. These estimation accuracies are validated with high-fidelity camera-in-the-loop simulations of angles-only navigation in an eccentric Mars orbit. For a proposed four-spacecraft swarm taking distributed atmospheric measurements, ARTMS displays robust navigation across a variety of formations and under challenging measurement conditions, and achieves the necessary performance to support mission objectives.

1. INTRODUCTION

DISTRIBUTED space systems and spacecraft swarms in particular can offer many advantages when compared to traditional monolithic spacecraft, including improved accuracy, coverage, flexibility, robustness, and the ability to achieve entirely new scientific objectives [1]. In recent years, this has been evidenced by a variety of Earth-orbiting missions such as GRACE (NASA), TanDEM-X (DLR) and MMS (NASA), which have employed multiple cooperative satellites with great success [2] [3] [4]. Subsequently, there has been strong interest in the application of distributed systems for space exploration and in deep space environments. Of special interest is the use of nanosatellite technology, with the aim of leveraging miniaturized hardware to achieve ambitious performance at vastly reduced costs. Proposed deep space missions that demonstrate these aspects include the Autonomous Nanosatellite Swarming project, which aims to characterize an asteroid using a swarm of CubeSats [5], and the NASA Starling program, which has suggested applying CubeSat swarms for lunar exploration, communications and monitoring [6]. Proposed Earth-orbiting CubeSat swarm missions include the Space Weather Atmospheric Reconfigurable Multiscale Experiment (SWARM-EX), which will study the ionosphere and thermosphere [7], and the Virtual Super Optics Reconfigurable Swarm (VISORS), which will implement a distributed solar telescope [8].

Nevertheless, the navigation of swarms in deep space presents significant technological challenges. Current formation-flying missions generally rely on Global Navigation Satellite System (GNSS) availability or frequent ground contacts for navigation. In contrast, swarms in deep space must aim to navigate with a high degree of autonomy, using only onboard resources. A promising solution in this regard is spaceborne angles-only navigation, in which observer satellites measure bearing angles to fellow swarm members via onboard vision-based sensors (VBS). Cameras are passive, robust, low size-weight-power-cost sensors already present on the majority of spacecraft, conducive to both accurate navigation and swarm miniaturization. They also offer high dynamic range and are applicable to swarms operating at inter-spacecraft separations from several kilometers to several thousand kilometers. Figure 1 presents an example of a VBS image.

As documented in literature, two prior flight experiments have demonstrated angles-only navigation in orbit. In 2012, the Advanced Rendezvous using GPS and Optical Navigation (ARGON) experiment enabled the rendezvous of two smallsats in low Earth orbit (LEO) from inter-satellite sep-
Development at NASA Ames Research Center [6]. Its ap-
part of the Starling technology demonstration mission under
Formation-flying Optical eXperiment (StarFOX), which is
ARTMS will initially be flight tested in LEO by the Starling
must possess a VBS and an ISL.
requirements posed on a spacecraft by ARTMS are that it
must observe in any planetary orbit regime. It is divided into three
modules based on angles-only algorithms recently developed at SLAB: image processing [18], batch orbit determination [19], and sequential orbit determination [16]. Each module operates with minimal a-priori information and applies absolute and relative state knowledge as it becomes available. ARTMS also exploits sharing of measurements over an intersatellite link (ISL) to enable use of multiple observers for navigation. Overall, ARTMS provides orbit estimates for the host spacecraft and each target detected by its onboard VBS, as long as each swarm observer is provided with an estimate of its absolute orbit at a single epoch. The only hardware requirements posed on a spacecraft by ARTMS are that it must possess a VBS and an ISL.
ARTMS will initially be flight tested in LEO by the Starling Formation-flying Optical eXperiment (StarFOX), which is part of the Starling technology demonstration mission under development at NASA Ames Research Center [6]. Its ap-
pliability to deep space has also been studied as part of a collaboration between SLAB and the NASA Jet Propulsion Laboratory. An example of a new mission concept enabled by ARTMS is a swarm of CubeSats taking distributed measurements of Mars’ atmosphere, thermosphere, ionospheric plasmas, and transient magnetic fields. Such a swarm could be deployed from a primary spacecraft to enable greatly enhanced science return at minimal additional cost. Angles-only navigation can also be applied in secondary fashion – for instance, as a secondary navigation system for pairs of small satellites taking interferometric synthetic aperture radar (SAR) measurements of the Martian surface, or in the form of a swarm of CubeSats that provide an external orbit estimate for a larger, Mars-orbiting flagship spacecraft.

In light of this range of potential applications, this paper presents usage of the ARTMS architecture for autonomous, multi-observer angles-only navigation of spacecraft swarms around planetary bodies. Three primary contributions to the state of the art are presented. First, the ARTMS architecture and algorithms are presented, with specific focus on the operational capabilities that are necessary to enable deep space navigation and new mission concepts. This includes implementation of new multi-observer measurement assignment algorithms and estimation of the clock drifts between swarm observers using angles-only measurements. Second, a quantitative observability analysis of multi-observer angles-only navigation in Mars orbit is presented, via computation of the estimated state covariance using a measurement noise matrix (representative of expected sensor performance) and a measurement sensitivity matrix across all measurement epochs. This analysis indicates that both absolute and relative swarm orbit determination can be achieved using intersatellite angles-only measurements. Third, the estimation accuracies from the observability analysis are validated through simulations of angles-only navigation in Mars orbit using ARTMS. An example Mars swarm science mission is developed, enabled by purely angles-only navigation. Camera-in-the-loop simulations of several representative navigation scenarios demonstrate sufficient navigation accuracy and robustness to achieve the stated science goals under challenging measurement conditions. ARTMS is therefore considered a promising solution for missions aiming to apply spacecraft swarms and their advantages in deep space environments.

The paper is organised as follows. After this introduction, Section 2 presents necessary mathematical background in regards to the measurement model, dynamics model, and estimated swarm state. Section 3 describes operational considerations for swarm navigation in deep space, with reference to potential mission applications. Section 4 introduces the ARTMS architecture and the algorithms necessary to enable robust, autonomous navigation in deep space. Section 5 presents the swarm observability analysis and relevant results. Section 6 details the simulated Mars mission and data generation pipeline, along with a discussion of results. Section 7 contains concluding remarks.

2. Modelling Preliminaries

Measurement Model
The ARTMS payload produces angles-only measurements by computing the time-tagged bearing angles to objects detected in VBS images. Bearing angles consist of azimuth and elevation (α, ε) and subtend the line-of-sight vector $\delta r^V = (\delta r_x^V, \delta r_y^V, \delta r_z^V)$ from the observer to the target. Superscript
\( \mathcal{V} \) indicates that the vector is described in the observer VBS coordinate frame. This frame consists of orthogonal basis vectors \( \hat{x}, \hat{y}, \hat{z} \) where \( \hat{z} \) is aligned with the camera boresight and \( \hat{z}^V = \hat{x} \times \hat{y}^V \). Bearing angles are then computed via [20]

\[
(\alpha V) = \left( \arcsin \frac{\delta r_y}{\|\delta r\|}, \arctan \frac{\delta r_x}{\delta r_z} \right)
\]

(1)

Bearing angles can be related to the inertial frame by rotating \( \delta^V \) into the planet-centered inertial (PCI) frame \( \mathcal{P} \), as per

\[
\delta^P = \mathcal{V} \mathcal{P} \delta^V
\]

(2)

where \( \mathcal{V} \mathcal{P} \) denotes a rotation from frame \( \mathcal{V} \) into frame \( \mathcal{P} \). This rotation matrix is computed by performing attitude determination using stars identified by the VBS [9].

It is also useful to define the radial/along-track/cross-track (RTN) frame of the observer, denoted \( \mathcal{R} \). It is centered on and rotates with the observer and consists of orthogonal basis vectors \( \hat{x}^R \) (directed along the observer’s absolute position vector); \( \hat{y}^R \) (directed along the observer’s orbital angular momentum vector); and \( \hat{z}^R = \hat{x}^R \times \hat{y}^R \) [21]. Similarly, define a frame \( \mathcal{W} \) using \( \hat{y}^W \) (directed along the observer’s velocity vector); \( \hat{z}^W = \hat{z}^R \); and \( \hat{x}^W = \hat{y}^W \times \hat{z}^W \). \( \mathcal{W} \) only differs from \( \mathcal{R} \) by a rotation of the observer flight path angle \( \phi_f \) about \( \hat{z}^W \) with \( \phi_f \approx 0 \) in near-circular orbits [21]. Figure 2 depicts the relationship between coordinate frames and bearing angles. Rotation matrices \( \mathcal{R} \mathcal{P} \) and \( \mathcal{W} \mathcal{P} \) can be computed using the observer’s absolute orbit estimate.

\textbf{Figure 2.} Definition of the target line-of-sight vector and bearing angles with respect to \( \mathcal{V}, \mathcal{R} \) and \( \mathcal{W} \). Here, the VBS points in the anti-velocity direction.

\textbf{State Parametrization}

ARTMS represents the absolute state \( \alpha \) of the observer in terms of quasi-nonsingular orbit elements (OE), with

\[
\alpha = \begin{pmatrix} a \\ e_x \\ e_y \\ \Omega \\ u \end{pmatrix} = \begin{pmatrix} a \\ e \cos \omega \\ e \sin \omega \\ \Omega \\ \omega + M \end{pmatrix}
\]

(3)

Above, \( a, e, i, \Omega, \omega \) and \( M \) are the canonical Keplerian OE of semi-major axis, eccentricity, inclination, right ascension of the ascending node, argument of perigee, and mean anomaly respectively, and \( u \) is the mean argument of latitude.

The relative orbit \( \delta \alpha \) of a target spacecraft, as tracked by an observer, is described by the quasi-nonsingular relative orbit elements (ROE) proposed by D’Amico [22]. The ROE state parametrization is defined in terms of the absolute OE of the observer and target (denoted by subscripts ‘o’ and ‘t’ respectively) via

\[
\delta \alpha = \begin{pmatrix} \delta a \\ \delta \lambda \\ \delta e_x \\ \delta e_y \\ \delta \Omega \\ \delta \iota \\ \delta \phi \end{pmatrix} = \begin{pmatrix} (a_t - a_o)/a_o \\ (\Omega_t - \Omega_o) \cos \iota_o \\ e_{x,t} - e_{x,o} \\ e_{y,t} - e_{y,o} \\ \iota_t - \iota_o \\ (\Omega_t - \Omega_o) \sin \iota_o \end{pmatrix}
\]

(4)

Above, \( \delta a \) is the relative semi-major axis, \( \delta \lambda \) is the relative mean longitude, \( \delta e = (\delta e_x, \delta e_y) \) is the relative eccentricity vector with magnitude \( \delta e \) and phase \( \phi \), and \( \delta \hat{e} = (\delta e_x, \delta e_y) \) is the relative inclination vector with magnitude \( \delta i \) and phase \( \theta \). Fully nonsingular ROE have also been defined for equatorial orbits [23].

The ARTMS state also includes several optional components. First are absolute empirical accelerations for the observer spacecraft and differential empirical accelerations for target spacecraft, defined as

\[
a_{\mathcal{R}}^{\mathcal{E}mp} = \begin{pmatrix} a_x \\ a_y \\ a_z \end{pmatrix}
\]

(5)

\[
\delta a_{\mathcal{R}}^{\mathcal{E}mp} = \begin{pmatrix} \delta a_x \\ \delta a_y \\ \delta a_z \end{pmatrix} = \begin{pmatrix} a_{x,t} - a_{x,o} \\ a_{y,t} - a_{y,o} \\ a_{z,t} - a_{z,o} \end{pmatrix}
\]

(6)

respectively. Empirical accelerations are used to approximately capture unmodeled dynamics in a more computationally efficient fashion than numerically integrating the full differential equations of relative motion [20], and are defined in the RTN frame. The second set of optional state components are the absolute clock errors and clock drift rates of the observer, and differential clock errors and clock drift rates of targets with respect to the observer, defined as

\[
c_{\mathcal{R}}^{err} = \begin{pmatrix} c_{\mathcal{R}}^{err} \\ d_{\mathcal{R}}^{err} \end{pmatrix}
\]

(7)

\[
\delta c_{\mathcal{R}}^{err} = \begin{pmatrix} \delta c_{\mathcal{R}}^{err} \\ \delta d_{\mathcal{R}}^{err} \end{pmatrix} = \begin{pmatrix} c_{\mathcal{R},t}^{err} - c_{\mathcal{R},o}^{err} \\ d_{\mathcal{R},t}^{err} - d_{\mathcal{R},o}^{err} \end{pmatrix}
\]

(8)

Above, \( c_{\mathcal{R}}^{err} \) is a clock drift and \( d_{\mathcal{R}}^{err} \) is a clock drift rate. For \( n \) detected targets, the complete ARTMS state is therefore

\[
x = (\alpha, a, c, \delta \alpha_1, \delta a_1, \delta c_1, \ldots, \delta \alpha_n, \delta a_n, c_n)
\]

(9)

Additional state components — such as VBS sensor biases or spacecraft ballistic properties — can also be estimated using ARTMS algorithms [16] but are not included here.

\textbf{Dynamics Model}

ARTMS propagates the absolute orbits of observer and target spacecraft using Euler integration of Gauss’ variational equations, including all major perturbations for the considered orbit. For the state \( \alpha \), the osculating OE of each spacecraft
The near-circular case was extended to eccentric orbits

\[ \delta \]

D’Amico’s ROE for various terms are alternately used when computational efficiency is paramount, including the mean OE are defined in the RTN frame. Analytic dynamics models for the magnitudes of offsets in the radial and along-track directions respectively; magnitudes of the ROE and the target’s curvilinear position vector circular orbits [22], who formulated a linear map between analytic dynamics models for the ROE state [23] [25].

A particularly useful aspect of the ROE is that they provide particularly useful aspects that the angles-only system must possess. First consider usage of angles-only as the primary navigation method for a novel swarm science mission, taking cooperative, distributed or repeating measurements at varying scales impossible with a single spacecraft. If extremely high positioning accuracy is not required, purely angles-only methods are sufficient. Example objectives include characterization of planetary atmospheres and ionospheres [7], solar wind measurements [6], and visual surveys. Angles-only navigation can also be employed in a secondary fashion. Consider pairs of satellites using interferometric SAR to map planetary surfaces, for which inter-spacecraft separations must be known to centimeter-level accuracy [3]. Angles-only navigation may not be able to achieve this alone, but can still be used to support mission operations, such as during safe modes, low power modes, or formation acquisition. Furthermore, angles-only techniques could be leveraged to support a larger, flagship spacecraft via ‘navigation buddies’, i.e. a swarm of small satellites deployed from the flagship to provide absolute orbit determination in a robust, real-time, cooperative manner. This swarm could be temporary, reusable, or a permanent companion, and could even carry science instruments itself. More ambitious scales can also be explored. Consider a planetary optical navigation service, in which a constellation of small satellites acts as optical beacons for other ground-based or orbiting assets. If the constellation maintains prescribed orbits, other assets may use bearing angle measurements to triangulate their positions in a fashion similar to GNSS. Such a system could be used to support growing manned or unmanned exploration efforts around Mars, with potentially lower costs (but also lower accuracy) than a traditional GNSS system.

When introducing ARTMS, it is thus useful to consider types of multi-satellite mission which are enabled by angles-only technologies, and the resulting operational constraints that must be met.

First, consider usage of angles-only as the primary navigation method for a novel swarm science mission, taking cooperative, distributed or repeating measurements at varying scales impossible with a single spacecraft. If extremely high positioning accuracy is not required, purely angles-only methods are sufficient. Example objectives include characterization of planetary atmospheres and ionospheres [7], solar wind measurements [6], and visual surveys. Angles-only navigation can also be employed in a secondary fashion. Consider pairs of satellites using interferometric SAR to map planetary surfaces, for which inter-spacecraft separations must be known to centimeter-level accuracy [3]. Angles-only navigation may not be able to achieve this alone, but can still be used to support mission operations, such as during safe modes, low power modes, or formation acquisition. Furthermore, angles-only techniques could be leveraged to support a larger, flagship spacecraft via ‘navigation buddies’, i.e. a swarm of small satellites deployed from the flagship to provide absolute orbit determination in a robust, real-time, cooperative manner. This swarm could be temporary, reusable, or a permanent companion, and could even carry science instruments itself. More ambitious scales can also be explored. Consider a planetary optical navigation service, in which a constellation of small satellites acts as optical beacons for other ground-based or orbiting assets. If the constellation maintains prescribed orbits, other assets may use bearing angle measurements to triangulate their positions in a fashion similar to GNSS. Such a system could be used to support growing manned or unmanned exploration efforts around Mars, with potentially lower costs (but also lower accuracy) than a traditional GNSS system.

In view of these examples, there are three broad operational capabilities that the angles-only system must possess. First is distribution, in that the navigation architecture should be capable of providing navigation for arbitrary numbers of
swarm observers and swarm targets, and allow distributed or decentralized operation. By taking maximum advantage of distributed measurement and processing capabilities, the overall reliability, flexibility and scalability of navigation for deep space mission concepts can be improved. This also relates to a primary driver behind the adoption of swarm-based concepts and spacecraft miniaturization, i.e. that there is potential for groups of small satellites to achieve enhanced capabilities at lower cost and on faster timelines [1]. Thus, navigation should be achievable with minimal hardware suitable for small satellites or nanosatellites in regards to sensing, communications bandwidth, and processing power. This is supported by use of angles-only and vision-based sensors, which are cheap, low mass, low power systems. In comparison, the efficacy of (for example) inter-satellite ranging is potentially limited for nanosatellite hardware.

Second, for the above concepts, there is a strong preference for autonomy and the ability to navigate using only onboard sensors and resources. Traditionally, deep space navigation has relied on external measurement frameworks such as the NASA Deep Space Network (DSN). However, the increasing number of interplanetary spacecraft has placed strain on these navigation capabilities — strict scheduling is already necessary to ensure spacecraft can receive appropriate and timely navigation solutions [26]. This only becomes more difficult for swarms. If each spacecraft in the swarm requires individual contact with the DSN, navigation rapidly becomes extremely inefficient or untenable. Ultimately, future swarm navigation methods should require minimal ground contact, in the sense of being self-initializing, self-sustaining and self-contained. Existing angles-only architectures have been unable to achieve this, however, in that they require accurate a-priori relative orbit information for navigation initialization and regular external absolute orbit updates to maintain state convergence [9] [10] [16]. Furthermore, if ground updates are sparse, it becomes necessary to estimate additional state components such as the clock errors of swarm observers, which has not been treated by prior work in this field.

Third, navigation must guarantee a high degree of robustness and sufficient accuracy to achieve mission goals — especially for interplanetary missions which incur significant cost and investment. From a hardware perspective, angles-only solutions are again attractive because cameras are simple, passive, robust and accurate. However, robustness of estimation has proven challenging. Prior work has shown that bearing angle measurements from a single observer do not distinguish between a change in the mean argument of latitude ($\delta_\lambda$) of the observer and the mean longitude ($\lambda_0$) of a target, creating an unobservable mode which can lead to gradual state divergence [19]. Furthermore, angles-only navigation for spacecraft is characterized by weak observability because bearing angles do not contain explicit target range information [27] [28]. It has thus been suggested to use frequent translational maneuvers to disambiguate target range, but this limits mission lifetime from associated propellant use (and additionally reduces autonomy by requiring maneuver plans). More broadly, deep space navigation systems should also be robust to errors in the state estimate or a-priori information, and agnostic to absolute and relative orbit geometries and the specific planetary dynamic environment.

4. ARTMS ARCHITECTURE

In response to these considerations, a novel navigation architecture has been developed by Stanford’s SLAB. “ARTMS” is a self-contained software payload that provides autonomous, distributed angles-only navigation for spacecraft swarms in planetary orbit regimes [16] [17]. To describe its structure, the following terminologies are adopted. The “observer” refers to the spacecraft hosting the instance of the ARTMS payload being discussed. A “remote observer” is another spacecraft hosting an ARTMS payload that is providing measurements over the ISL. The “local swarm” includes the observer and all “targets”, which are spacecraft detected by the onboard VBS. Often, targets will include one or more remote observers. Figure 4 presents an example.

A high-level overview of ARTMS is shown in Figure 5. ARTMS consists of of three core software modules, in green: Image Processing (IMP), Batch Orbit Determination (BOD) and Sequential Orbit Determination (SOD). ARTMS also interfaces with several core data sources, in gray. The VBS provides time-tagged images to the payload; the ISL communicates orbit estimates and bearing angle measurements between all swarm observers; the spacecraft bus provides additional attitude information; and the ground segment provides telecommands for each observer in the swarm and receives telemetry from ARTMS instances. In this paper, it is assumed GNSS measurements are unavailable.

Operation of each module is briefly described as follows. First, the IMP module uses images from the VBS to produce batches of bearing angle measurements with corresponding uncertainties for all detected targets in the FOV. The only prior information needed is a coarse estimate of the observer’s absolute orbit at a single epoch, provided by a source such as the DSN. IMP measurement batches are provided to BOD and SOD. The BOD module uses the IMP angle batches, as well as the aforementioned estimate of the observer’s orbit, to compute state estimates for all spacecraft in the local swarm (including itself and all targets observed by the VBS). This state estimate is provided to the SOD module for initialization and fault detection. The SOD module uses the BOD state estimate to initialize an unscented Kalman filter (UKF), which fuses measurements from IMP and remote ISL observers to refine the orbit estimates of all spacecraft in the local swarm (as well as auxiliary parameters such as ballistic coefficients or differential clock offsets). State updates from known maneuvers are applied if necessary. SOD then provides updated state estimates to IMP to more efficiently assign bearing angles in new images to existing targets. The orbit estimate and bearing angles are also sent to the ISL. Sample times for each module are approximately one minute for IMP and VBS measurements, once per orbit for BOD, and one minute for SOD.

Overall, the structure of this architecture is intended to treat the aforementioned operational constraints. Distribution and
swarming are achieved in that the algorithms are scalable to arbitrary numbers of observers and targets, and navigation is distributed between observers via sharing of local measurements and state estimates over the ISL. The structure of the three modules is such that ARTMS requires essentially no support from ground-based resources. IMP applies novel data association algorithms, in concert with BOD estimation algorithms, to enable self-initialization of navigation with a single external absolute orbit measurement per observer. Modules subsequently take advantage of additional information as it becomes available to enable near-total autonomy. Of particular importance, with respect to prior work, is the application of multiple observers. SOD employs new algorithms to match measurements from different observers to corresponding targets, and the resulting stereo measurements vastly improve state estimate robustness, convergence and accuracy. Unobservable modes are removed and it becomes much easier to disambiguate target range. Thus, ARTMS is able to estimate both the absolute and relative orbits of the swarm with exclusively bearing angles, eliminating reliance on maneuvers and external measurement sources.

The IMP, BOD and SOD algorithms are presented in more detail in the following section, with more information available in [18], [19] and [16] respectively.

**Image Processing**

The objective of IMP is to produce batches of time-tagged bearing angle measurements to each target using a coarse estimate of the observer’s orbit and images provided by the onboard VBS. This is accomplished in two phases. First, each incoming image is processed and reduced to a set of inertial bearing angles that may correspond to resident space objects. Second, these candidate bearing angles are used to track known targets and detect new targets using an approach inspired by multi-hypothesis tracking (MHT) [12].

The first phase of IMP uses a set of well-known algorithms. First, a centroiding algorithm is used to simplify the raw image into a list of pixel cluster centroids [29]. Second, these centroids are converted to unit vectors in the sensor frame using the calibrated sensor model. Next, the pyramid star identification algorithm [30] is applied to remove stellar objects (SO) from the list of pointing vectors. Uncatalogued SO are detected by considering objects with unchanging inertial unit vectors between images. Similarly, camera hotspots are removed by considering objects with unchanging pixel coordinates. The VBS attitude is computed from the pointing vectors to identified stars in the inertial and sensor frames using the q-method [31]. The remaining minimal set of inertial unit vectors (and corresponding bearing angles in the sensor frame) likely correspond to known targets or other unknown objects in the field of view (FOV).

In the second phase, measurements must be assigned to targets currently being tracked or used to initialize new targets, without requiring a-priori relative orbit knowledge. To accomplish this, the IMP module employs the new Spacecraft Angles-only MUltitarget tracking System (SAMUS) algorithm [18], which has two key requirements: 1) a coarse estimate of the observer’s absolute orbit is provided, and 2) targets do not perform large translational maneuvers during the tracking period. SAMUS has been specifically designed to meet the constraints of risk-averse angles-only navigation in space, i.e. to achieve close to 100% measurement assignment precision with low measurement frequencies and limited computational resources. It applies the core concept of MHT in that as measurements arrive, many simultaneous hypotheses are maintained as to how they can be associated into target tracks. The algorithm converges towards the correct hypothesis over time. MHT is chosen as a basis because it is mature and demonstrably accurate, with its primary disadvantage being the need to frequently and heuristically trim hypotheses for real-time computation [32]. To overcome this, SAMUS applies domain-specific knowledge to develop precise trimming criteria.

These criteria stem from Equation 12, which defines a map-
ping between the target’s curvilinear position vector in RTN and its eccentric ROE. In this mapping, note that true anomaly $f_o$ is the only quickly-varying term. Other terms, as defined by the OE and ROE, vary slowly in the presence of perturbations such as spherical harmonic gravity and atmospheric drag [22]. In most angles-only scenarios of interest, however, swarm members are in relatively close proximity in inertial space and are thus affected similarly by perturbations. By synchronously differencing the measured unit vectors of different targets in RTN – in essence, using one target’s track as a virtual, moving origin for another – perturbation effects are approximately cancelled between targets. After this transformation, target motion in the RTN frame (or equivalently, in bearing angle space) is described by Equation 12, but now all terms other than $f_o$ can be considered constant on the scale of image-to-image tracking. Thus, target motion is periodic with known form, dependent on parameter $f_o$. Even if specific values of the relevant ROE are unknown, this expectation can be leveraged to assess hypotheses.

The first important tool derived from Equation 12 is a method by which to fit this model to tracks of measurements. The model can then be used to assess goodness of fit and predict upcoming measurements. Given $i = 1, \ldots, n$ past bearing angles in a track, Equation 12 can be rearranged into a pair of separable linear systems in azimuth and elevation, via [18]

\[
\begin{bmatrix}
  x_{1,1} & x_{1,2} & x_{1,3} \\
  \vdots & \vdots & \vdots \\
  x_{n,1} & x_{n,2} & x_{n,3} \\
\end{bmatrix}
\begin{bmatrix}
  y_1 \\
  y_2 \\
  y_3 \\
\end{bmatrix}
= \begin{bmatrix}
  \epsilon_1 \\
  \epsilon_2 \\
  \epsilon_3 \\
\end{bmatrix}
\]

(14)

\[
\begin{bmatrix}
  x_{1,4} & x_{1,5} & x_{1,6} \\
  \vdots & \vdots & \vdots \\
  x_{n,4} & x_{n,5} & x_{n,6} \\
\end{bmatrix}
\begin{bmatrix}
  y_4 \\
  y_5 \\
  y_6 \\
\end{bmatrix}
= \begin{bmatrix}
  \alpha_1 \\
  \alpha_2 \\
  \alpha_3 \\
\end{bmatrix}
\]

(15)

The $x_{i,j}$ values are computed using the one-off observer absolute orbit estimate, numerically propagated into each measurement epoch. The unknown $y_{i,j}$ terms are scaled ROE equivalents in bearing angle space and can be solved for via least squares as long as at least three past measurements exist. Subsequently, upcoming measurements in a new image can be predicted.

The second tool is a set of kinematic rules, which are applied to assess which hypotheses are physically reasonable. Only tracks which pass all rules are propagated. Briefly, the rules are summarised as:

1. Track velocities must be below a set maximum
2. Track velocities must be consistent over time
3. Tracks should generally not feature acute angles
4. Tracks should turn in a consistent direction
5. New data must be close to the predicted measurement

Their application greatly increases efficiency of MHT by preventing formation of unlikely tracks. Mathematical definitions for these rules are provided in [18]. When multiple tracks pass all rules, SAMUS scores propagated tracks via ten criteria, which assess how well track each fulfills the expectations of Equation 12 and prior motion. In contrast to traditional MHT methods – which often rely on a single Mahalanobis distance metric for scoring – SAMUS aims to be more robust. Often, target tracks intersect or are in close proximity in the image plane, or motion between images is on the order of VBS noise. A single scoring metric is therefore not robust. By using a larger set of metrics, consensus supports the correct choice over time, even if some metrics temporarily support incorrect hypotheses. Additionally, scoring does not require probabilistic estimates of false alarm densities or target decay rates, which are not easily obtainable for spacecraft.

To initialize new tracks, SAMUS employs the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [33]. DBSCAN clusters require $\geq n_P$ points within small radius $\epsilon_P$. Because targets are in similar orbits to observers, their velocities compared to other objects in the FOV are low [10]. Previously untracked targets are initialized by applying DBSCAN to the merged set of unidentified measurements from the past several images, and applying the SAMUS kinematic rules to found clusters. Finally, given the use of visual measurements, tracking is often interrupted by orbit eclipse periods. To connect shorter tracks on either side of an eclipse, the linear system fit is computed for every possible set of paired tracks. The combination of compatible pairs which produces the least fitting residuals is chosen.

SAMUS is also able to cooperate with SOD and apply target state knowledge, if available. The state estimate from SOD is propagated and used to compute swarm absolute orbit estimates in the current epoch. Predicted target measurements are then computed. The kinematic rules are replaced by a validity region around the predicted measurement, from an unscented transform of the target state covariance. The Mahalanobis distance between predicted and assigned measurement is employed for track scoring. Maneuvers can also be tracked in this mode. Figure 6 presents an overview of core SAMUS operations.

**Figure 6.** SAMUS algorithm summary and core sequence of operations. Dashed lines denote steps that only occur at relevant epochs.

**Batch Orbit Determination**

The BOD module must be able to produce orbit estimates for the local swarm with sufficient accuracy to initialize the SOD module, using only a coarse estimate of the observer’s orbit and batches of bearing angles to each target from the onboard sensor. For simplicity, it is assumed that targets do not perform translational maneuvers while measurement batches are being collected. Typical collection periods are 1-2 orbits. State estimation is accomplished using a new algorithm [19] that sequentially estimates the relative orbits of each target while simultaneously refining the estimate of the semimajor axis of the observer’s orbit. The algorithm uses a fully analytical dynamics model to minimize computation cost. Note that the perturbations which must be included in the analytic model depend on the planetary environment.
example, in LEO, the $J_2$ oblateness perturbation is generally dominant. However, in low Mars orbit, the $J_3$ perturbation has comparatively more influence [34] and must also be included.

For each target, BOD state estimation is a four-step procedure that was inspired by the work of Ardaens [14]. First, a 1-D family of state estimates is computed for user-specified values of $\delta \lambda$, using iterative batch least squares refinement until either 1) a user-specified iteration limit is reached, or 2) the step size is smaller than a user-specified convergence threshold. Second, the final state estimate is selected as the candidate $\delta \lambda$ and resulting state estimate which produced the least measurement residuals. A typical choice of $\delta \lambda$ is to sample the expected state space in 1km intervals. A conceptual illustration of the BOD state selection process for a single target is shown in Figure 7, including measurement residuals for selected and rejected state estimates.

![Figure 7](image_url) Conceptual illustration of converged measurement residuals for rejected (gray) and selected (black) state estimates at specified values of $\delta \lambda$ for a single target in the BOD module.

Third, the measurement noise matrix for each measurement (denoted $R_{vbs}$) is estimated using the measurement residuals corresponding to the final state estimate. Fourth, the covariance for estimated state components $P_{est}$ is computed, via

$$P_{est} = Y_{est}^*(NY_{vbs} + Y_{prior}P_{prior}Y_{prior}^TY_{est})Y_{est}^*$$

(16)

where $Y_{est}$ is the pseudoinverse of the measurement sensitivity matrix for estimated state components, $Y_{prior}$ is the measurement sensitivity matrix for a-priori information (e.g. orbit elements other than the semimajor axis, ballistic coefficients), $P_{prior}$ is the uncertainty of the a-priori information, and $N$ is the number of provided bearing angle measurements. This formulation allows the BOD module to seamlessly transition between domains where uncertainty is driven by sensor performance and by errors in the a-priori information. Finally, the ROE estimates for each target are appended to the refined estimate of the observer’s absolute orbit, forming a complete estimate of the state of the local swarm.

It was demonstrated in [19] that this estimation approach can provide relative orbit estimates with range errors of less than 20% (3-$\sigma$) in the presence of absolute orbit errors of up to 2 km using only two orbits of bearing angle measurements in a wide range of orbit regimes. Additionally, the computation time required to estimate the state of each target with two orbits of measurements is approximately five seconds on a desktop PC with a 3.5GHz processor using the analytical dynamics model. The computation cost increases linearly with the number of targets in the local swarm, allowing the algorithm to efficiently scale to large swarms.

**Sequential Orbit Determination**

The SOD module continually refines orbit estimates of all spacecraft in the local swarm, and auxiliary parameter estimates (e.g. sensor biases, ballistic coefficients, and differential clock offsets), by seamlessly fusing measurements from all observers transmitted over the ISL. The SOD module is based on the UKF, which preserves higher order moments in the probability distribution to enable maneuver-free convergence using angles-only measurements from a single observer [16]. Three additional features are included in the SOD module to to maximize performance. First, adaptive process noise estimation is used to improve convergence speed and robustness to errors in the dynamics model [35]. Second, the state definition is organized in a way that exploits the structure of the Cholesky factorization to reduce the number of calls to the orbit propagator by almost a factor of two [36]. Third, measurements from remote observers are assigned to locally-tracked targets using selection criteria based on the Mahalanobis distances between the estimated bearing angles to each target and each candidate measurement.

To enable remote observer measurement assignment, it is first necessary to know whether any of the locally-tracked targets are in fact remote observers. Let $\sigma_{mn}$ denote the Mahalanobis distance between the broadcast orbit estimate of remote observer $m$ and the predicted orbit estimate of local target $n$. To minimize erroneous assignments, remote observer $m$ is identified as target $n$ if four conditions are fulfilled:

1. $m$ has not yet been identified
2. $\sigma_{mn} \leq \epsilon_{id}$: remote observer $m$’s orbit is similar to the estimate of the target $n$’s orbit.
3. $\sigma_{mn} \geq \epsilon_{safe}$ $\forall$ $p \neq m$: there is no other remote observer that fits target $n$’s orbit.
4. $\sigma_{mq} \geq \epsilon_{safe}$ $\forall$ $q \neq n$: there is no other target that fits remote observer $m$’s orbit.

Identifications are kept until $\sigma_{mn} \geq \epsilon_{remove}$. Parameters are user-specified with $\epsilon_{remove} \geq \epsilon_{safe} > \epsilon_{id} > 0$. Formal target identification ensures that measurements by observer $m$ can never be considered as measurements of observer $m$—preventing this contradiction improves robustness and reduces the search space when assigning other measurements.

Next, measurements from the remote observer must be assigned to targets of the local observer. Let $\sigma_{ij}$ denote the Mahalanobis distance between measurement $i$ from the remote observer and the predicted measurement of local target $j$. To minimize erroneous assignments, measurement $i$ from the remote observer is assigned to local target $j$ if three conditions are satisfied:

1. $\sigma_{ij} \leq \epsilon_{assign}$: remote measurement $i$ is close to the modeled measurement of local target $j$.
2. $\sigma_{kj} \geq \epsilon_{ambig}$ $\forall k \neq i$: no other candidate measurement fits the estimated state of target $j$.
3. $\sigma_{ij} \geq \epsilon_{ambig}$ $\forall l \neq j$: no other local target fits remote measurement $i$.

The $\epsilon$ parameters are user-specified with $\epsilon_{ambig} > \epsilon_{assign} > 0$. Figure 8 includes conceptual illustrations of four possible cases of modeled and observed measurements from a remote observer which (from left to right) show all conditions satisfied and violations of Condition 1, Condition 2, and Condition 3, respectively. Together, these conditions ensure that measurements are only assigned when the observed and modeled measurements uniquely agree with a statistical
certainty determined by the values of $\epsilon_{assign}$ and $\epsilon_{ambig}$. The values of these parameters should be selected based on the expected number of targets, relative motion geometry, sensor noise, and available orbit knowledge for general swarming missions. However, for scenarios similar to those presented in the following section, the authors have found that setting $\epsilon_{id} = 3$, $\epsilon_{safe} = 6$, $\epsilon_{remove} = 10$, $\epsilon_{assign} = 3$ and $\epsilon_{ambig} = 6$ provide robust multi-observer identification.

![Figure 8. Illustration of conditions in which all measurement criteria are satisfied (left) and conditions that violate each of the measurement assignment criteria (right).](image)

**State Parametrization**

The choice of ARTMS state parametrization, as defined in Section 2, also provides crucial advantages. Firstly, use of the ROE to represent target states means that the weakly observable range to each target is primarily captured by the $\delta \lambda$ term in most swarm relative motion geometries, with other ROE components being strongly observable [37]. This allows ARTMS to maximize accuracy by applying separate state estimation techniques to different components, as is done for BOD. Second, the UKF in SOD is able to incorporate nonlinearities in the dynamics and measurement models in an efficient and accurate manner, which is leveraged to completely estimate observer and target states without maneuvers. Third, OE and ROE states vary slowly with time, which enables accurate numerical integration using Gauss’s variational equations with large time steps [38] for efficient onboard orbit propagation. Similarly, ROE have been well-studied in literature, resulting in the development of several accurate analytical dynamics models for Earth orbit [23] [25] that can be adapted to other planetary regimes.

The inclusion of differential clock drifts and clock drift rates between swarm observers in the estimated state further aids robustness and minimizes necessary ground contact. If clock drifts are not estimated or updated regularly, there will be significant measurement errors due to mismatches between the epochs of ISL measurements and the local ARTMS instance. This most prominently manifests as steady-state bias in $\delta \lambda$: a remote measurement being late or early is similar to the inter-satellite range appearing smaller or larger. Divergence in the absolute orbit estimate is also common if observer clocks are not synchronized. However, it is possible to account for clock differences within SOD. During target identification, measurement assignment, and measurement update steps, clock drifts are included by propagating the local state estimate to the estimated epoch of the relevant measurement. For local measurements, this is determined by the observer’s onboard clock. For remote measurements, this is the received time-tag plus the estimated differential clock drift for that observer.

**5. Observability Analysis**

To investigate the general feasibility of the ARTMS framework, it is useful to analyze overall system observability. The problem of simultaneously estimating the absolute orbit of an observer and relative orbit of a target with angles-only measurements has been recently examined by Hu [15] and Koenig [19], but only for a single observer. Hu concluded that this case was not fully observable, while Koenig likewise demonstrated that the complete absolute orbit of the observer could not be accurately estimated. However, the multi-observer case has not yet been explored, and prior studies have focused on Earth orbit. Extending this analysis to multiple observers in Mars orbit provides a quantitative indication of which state components can be estimated to useful accuracy. To enable comparison with prior work, this paper applies a similar methodology to Koenig et al. [19]. In essence, a state covariance matrix is computed from a measurement sensitivity matrix and a measurement noise matrix, which is used to determine the precision to which state components can be estimated.

**Numerical Observability Model**

Consider a model providing inertial bearing angle measurements $\mathbf{z}$ as a function of swarm state $\mathbf{x}$, local observer $o$, estimation epoch $t_{est}$, and measurement epoch $t$, of the form

$$\mathbf{z}(t) = h(\mathbf{x}, o, t_{est}, t)$$

Let bearing angles be provided at $N$ epochs $t_1, ..., t_N$, collectively referred to as $t_{est}$. Additionally, let there be $M$ swarm observers $o_1, ..., o_M$, collectively referred to as $o$. Define the clock error $\epsilon_{err}(o, t)$ of observer $o$ at epoch $t$. Then, the batch of measurements received by a single observer from all swarm observers at specific epoch $t$ is

$$\mathbf{y}_o(t) = \begin{pmatrix} h(\mathbf{x}, o_1, t_{est}, t + \epsilon_{err}(o_1, t)) \\ \vdots \\ h(\mathbf{x}, o_M, t_{est}, t + \epsilon_{err}(o_M, t)) \end{pmatrix}$$

and across all epochs, the batch of measurements received by a single observer from all swarm observers is

$$\mathbf{y} = g(\mathbf{x}, o, t_{est}, t_m) = \begin{pmatrix} \mathbf{y}_o(t_1) \\ \vdots \\ \mathbf{y}_o(t_N) \end{pmatrix}$$

Here, the measurement model is obtained by Euler integration of the orbits of all swarm members from $t_{est}$ to each measurement epoch, using the dynamics model in Equation 10. Measurements are computed from the propagated states.

It is then necessary to evaluate the partial derivatives of measurements with respect to each component of $\mathbf{x}$, for

$$\mathbf{Y}_{est}(\mathbf{x}) = \frac{\partial g(\mathbf{x}, o, t_{est}, t_m)}{\partial \mathbf{x}_{est}} |_{\mathbf{x}}$$

where $\mathbf{x}_{est}$ are the estimated components of $\mathbf{x}$. The partial derivatives for each specific measurement are computed numerically via central difference, using

$$\frac{\partial h}{\partial \mathbf{x}} |_{\mathbf{x}} = \frac{h(\mathbf{x} + \Delta \mathbf{x}, o, t_{est}) - h(\mathbf{x} - \Delta \mathbf{x}, o, t_{est})}{2||\Delta \mathbf{x}||}$$

where $\Delta \mathbf{x}$ is a vector that is zero except for the specific state component where sensitivity is being evaluated. Sizes used
for the central difference are 10m for the semimajor axis, 10m/\sqrt{a_o} for the other OE, 1m/\sqrt{a_o} for all ROE, 0.1 for clock drift, and 1e-5 for clock drift rate.

The observability analysis is based on the following model [19] for the relationship between the covariance matrix \( R \) for the complete measurement batch, and the covariance matrix \( P_\text{est} \) for the estimated state, given by

\[
R = Y_\text{est}(x)P_\text{est}Y_\text{est}^T(x)
\]  

(22)

When \( Y_\text{est} \) is full column rank – as is the case for all scenarios here – \( P_\text{est} \) can be computed as

\[
P_\text{est} = (Y_\text{est}^T(x)Y_\text{est}(x))^{-1}(Y_\text{est}^T(x)RY_\text{est}(x))
\times

(Y_\text{est}^T(x)Y_\text{est}(x))^{-1}
\]  

(23)

An advantage of computing \( P_\text{est} \), compared to evaluating the Lie derivatives or observability Gramian, is that accuracy requirements can be related to specific terms of \( P_\text{est} \). The matrix \( R \) follows the formulation in [19], which assumes independent measurements with identical noise distributions, no uncertainty in a-priori state information, and perfect knowledge of dynamics. \( P_\text{est} \) thus provides an indication of a lower bound for achievable estimation accuracy. If \( R_1 \) is the measurement noise matrix for a single measurement, \( R \) is

\[
R = \begin{bmatrix}
R_1 & 0 & \cdots & 0 \\
0 & R_1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & R_1
\end{bmatrix}
\]  

(24)

Below, observability of the complete swarm state is evaluated for six configurations:

1. Two swarm members, with one observer
2. Two swarm members, all observers
3. Three swarm members, with two observers
4. Three swarm members, all observers
5. Four swarm members, with two observers
6. Four swarm members, all observers

Each observer takes measurements of all other swarm spacecraft. Additionally, two different absolute orbits are explored: a near-circular low Mars orbit reminiscent of Mars Odyssey [39], and an eccentric Mars orbit reminiscent of MAVEN [40]. Two different relative orbit geometries are also tested: one that provides long-term passive safety via relative eccentricity/inclination (E/I) vector separation (typical of formation flying missions) [22], and an in-train (IT) formation that provides near-constant along-track separation (a common but less observable scenario) [15]. Tables 1 and 2 present the relevant OE and ROE. As identified in these tables, the first and second configuration consist of spacecraft 1 and 2; the third and fourth configurations consist of spacecraft 1 to 3; and the fifth and sixth consist of spacecraft 1 to 4. In the third configuration, spacecraft 1 and 3 are observers. In the fifth configuration, spacecraft 1 and 4 are observers. Table 3 presents the clock drifts used for each observer.

Bearing angles are assumed to be subject to 20 arcsec of 1-\( \sigma \) noise, with \( R_{\delta} = 9.4e-9 \times J_{\text{arc}}.2 \). This is representative of errors from modern nanosatellite star tracker cameras [41]. Two orbits of measurements are provided, with 50 measurements per orbit at evenly-spaced intervals. The dynamics model for numerical propagation applies a 4x4 Mars GMM-3 gravity model [34], a cannonball drag model with an exponential approximation of Mars atmospheric density [42], a cannonball solar radiation pressure model with cylindrical Mars shadow, and third-body Sun gravity. The integration timestep is 30s. Each spacecraft is physically modelled as a 12U CubeSat.

### Numerical Results

First, it is useful to investigate how the estimation of different state subsets affects overall observability and estimation performance. The second multi-observer configuration (three spacecraft, two observers) is used, in a near-circular orbit and E/I-vector separated formation. Four possible sets of state components are evaluated: 1) only target ROE, 2) target ROE and observer differential clock offsets, 3) observer OE and target ROE, and 4) the complete state. The 1-\( \sigma \) uncertainty for each subset is provided in Table 4. If a state component is not part of the subset, it is denoted by ‘-‘ in the corresponding column. Uncertainties are computed by taking the square root of the corresponding element on the main diagonal of \( P_\text{est} \). When appropriate, they are scaled by the semimajor axis to provide a geometric interpretation of navigation accuracy. Quantities denoted by a bar indicate a mean uncertainty, averaged across all swarm observers and their tracked targets.

Several conclusions can be drawn. First, estimating the differential clock drifts and drift rates has little effect on the accuracy of the absolute and relative state estimates. This is evidenced by the very minor differences in accuracy between Columns 1 and 2, or Columns 3 and 4. Second, the addition of absolute state estimation does diminish the accuracy of relative state estimation. For example, uncertainty in \( \delta \lambda \) is three
times larger in Column 4 compared to Column 2. However, in contrast to prior work that investigated single observers only [19], it is apparent that the complete swarm state can be estimated with reasonable accuracy using multiple observers.

In Table 5, observability for different swarm configurations is explored. The complete swarm state is estimated, for the near-circular orbit and E/I-vector separated formation. Notice the very large uncertainties in \( \delta \lambda \), \( u \), \( \sigma_{\delta e} \), and \( \sigma_{\delta i} \) in Columns 1 and 2 — it is clear that Swarms 1 and 2 are unable to estimate the complete state. Swarm 2 does contain two observers, but both effectively measure equivalent but ‘mirrored’ bearing angles, which does not provide additional geometric information that could improve observability or distinguish unobservable modes. However, in Columns 3 and 4, the maximum uncertainties are less than 1 km. The complete state is observable once a third spacecraft is added, as in Swarms 3 and 4. This third spacecraft introduces an additional reference point that makes changes in the absolute and relative orbits geometrically unique, with respect to changes in bearing angles. Observability further improves in Columns 5 and 6, when adding more spacecraft and more observers to the swarm. However, the accuracy of clock estimation does slightly worsen with more observers because more clock errors must be taken into account. This is evidence when comparing the clock uncertainties in Column 3 with Column 4, or Column 5 with Column 6.

Table 6 presents observability results for different absolute and relative orbits. The complete state is estimated, using the four swarm members with two observers. The in-train formation in Column 2 sees noticeably diminished observability, in particular due to difficulty in distinguishing \( \delta a \) and \( \delta \lambda \). Nevertheless, reasonable accuracy is still achievable, due to the ability of multiple observers to take advantage of stereo measurements when determining target range. The eccentric orbit in Columns 3 and 4 improves observability for both formation types, and particularly benefits the in-train formation compared to Column 2’s near-circular case. The eccentricity introduces nonlinearities in the bearing angle measurements which improve overall observability.

The above analysis suggests that complete swarm states — including differential clock offsets — are observable using angles-only measurements, provided that multiple observers and at least three spacecraft are present. This provides useful guidelines as to when angles-only navigation is feasible and what level of accuracy can be potentially achieved. In ideal cases, using a four-spacecraft swarm, it may be possible to determine the absolute orbit to within 500m and relative orbits to within 0.2% of target range, after two orbits. In general, the least observable state components are \( \delta \lambda \), \( \Omega \) and \( u \), while conversely, \( a \) and the other ROE can be estimated with high precision. This matches the expected behavior of inter-satellite angles-only measurements: range \( \delta \lambda \) is weakly observable and is dependent on \( u \) and \( \Omega \), while the other ROE and resulting out-of-plane motion have much stronger effects on bearing angles.
6. MISSION SIMULATION

Proposed Mission

To validate the results of the observability analysis, and demonstrate the overall feasibility of autonomous angles-only swarm navigation, a simulation scenario is developed for a proposed Mars science mission. It presents an example of a future swarm mission which is enabled by angles-only navigation techniques. The mission consists of a swarm of four 12U CubeSats which take distributed measurements of the Martian atmosphere, thermosphere, ionospheric plasmas, and transient magnetic fields. By doing so, better understanding of Martian weather, atmospheric structure and ionospheric interactions can be achieved. These objectives are partly inspired by past missions such as NASA’s MAVEN spacecraft, which studies the atmosphere and ionosphere of Mars to provide insight into how the planet’s climate has changed over time [40]. Another source of inspiration is the upcoming SWARM-EX mission, which will use multiple cooperative CubeSats to measure ionized and neutral gases in the Earth’s upper atmosphere [7]. It applies a distributed measurement framework to observe atmospheric structure with varying temporal and spatial resolutions, thus taking advantage of a swarm to achieve objectives impossible with a single spacecraft. However, SWARM-EX is Earth-orbiting and will navigate with the aid of GNSS. In contrast, the proposed Mars swarm must navigate using bearing angles exclusively. Crucially, the objective of distributed atmospheric measurements does not require extremely precise swarm positioning knowledge. The mission can therefore be carried out using angles-only as the sole navigation method.

It is proposed that the swarm would be carried to Mars aboard a larger, primary spacecraft, and subsequently deployed by the primary spacecraft upon insertion into Mars orbit. The swarm first deploys into a simple in-train formation, whereupon it commences angles-only navigation. The swarm then reconfigures into a nominal science formation with E/I-vector separation between members. Over the course of the mission, the swarm executes regular planned reconfigurations (e.g. monthly) to achieve varying measurement baselines. Measurement data is broadcast to the primary spacecraft when in suitable proximity, which the primary spacecraft then relays to Earth. This is considered feasible as the science objective does not require particularly high data volumes. The only necessary ground contacts, from a navigation perspective, are telecommands to provide required ARTMS inputs, such as the single DSN absolute orbit initialization for each swarm observer, details of planned maneuvers, and specific algorithm parameters.

To provide a realistic example case, the absolute orbit of the simulated swarm is based on the 2020 orbit of MAVEN [40]. The orbit is eccentric with a period of approximately 3.5 hours, perigee altitude of 150 km, and apogee altitude of 4500 km. OE and ROE for a representative science formation are given Table 7. OE and ROE during deployment are given in Table 8. ROE are computed relative to Spacecraft 1. Note that two spacecraft are designated as permanent observers: Spacecraft 1 and 4. Other swarm members participate in science activity, but do not actively participate in navigation. Instead, they receive orbit estimates when needed from the observers. To enable consistent swarm observation, it is assumed that Spacecraft 1 maintains its attitude such that its camera boresight is consistently aligned with its local $\mathbf{y}^{WV}$ direction (i.e. the instantaneous velocity direction). Spacecraft 4 points its camera boresight in the $-\mathbf{y}^{WV}$ direction.

Table 7. Swarm configuration for mission science operations.

<table>
<thead>
<tr>
<th>OE</th>
<th>S/C 1</th>
<th>ROE</th>
<th>S/C 2</th>
<th>S/C 3</th>
<th>S/C 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$ (km)</td>
<td>5720</td>
<td>$\delta a$ (m)</td>
<td>-2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>$e$</td>
<td>0.38</td>
<td>$\delta \lambda$ (km)</td>
<td>20</td>
<td>40</td>
<td>60</td>
</tr>
<tr>
<td>$i$ (°)</td>
<td>75</td>
<td>$\delta e_x$ (m)</td>
<td>300</td>
<td>600</td>
<td>-800</td>
</tr>
<tr>
<td>$\Omega$ (°)</td>
<td>0</td>
<td>$\delta e_y$ (m)</td>
<td>300</td>
<td>600</td>
<td>-800</td>
</tr>
<tr>
<td>$\omega$ (°)</td>
<td>0</td>
<td>$\delta i_x$ (m)</td>
<td>200</td>
<td>-400</td>
<td>800</td>
</tr>
<tr>
<td>$M_0$ (°)</td>
<td>180</td>
<td>$\delta i_y$ (m)</td>
<td>200</td>
<td>-4000</td>
<td>800</td>
</tr>
</tbody>
</table>

Table 8. Swarm configuration for mission deployment operations.

<table>
<thead>
<tr>
<th>OE</th>
<th>S/C 1</th>
<th>ROE</th>
<th>S/C 2</th>
<th>S/C 3</th>
<th>S/C 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$ (km)</td>
<td>5720</td>
<td>$\delta a$ (m)</td>
<td>-2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>$e$</td>
<td>0.38</td>
<td>$\delta \lambda$ (km)</td>
<td>50</td>
<td>100</td>
<td>150</td>
</tr>
<tr>
<td>$i$ (°)</td>
<td>75</td>
<td>$\delta e_x$ (m)</td>
<td>30</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>$\Omega$ (°)</td>
<td>90</td>
<td>$\delta e_y$ (m)</td>
<td>40</td>
<td>-40</td>
<td>40</td>
</tr>
<tr>
<td>$\omega$ (°)</td>
<td>90</td>
<td>$\delta i_x$ (m)</td>
<td>30</td>
<td>-30</td>
<td>-30</td>
</tr>
<tr>
<td>$M_0$ (°)</td>
<td>0</td>
<td>$\delta i_y$ (m)</td>
<td>30</td>
<td>-30</td>
<td>-30</td>
</tr>
</tbody>
</table>

Figure 9 visualizes the absolute orbit of the swarm around Mars for the science formation. In this configuration, significant eclipse periods (yellow) and sun-blinding periods (red) are present for the onboard VBS. Approximately 50% of the orbit cannot supply angles-only measurements, presenting a challenging scenario for the navigation system. Figures 10 and 11 present target relative orbits, with respect to Spacecraft 1, for the science and deployment formation respectively.

A reconfiguration scenario is also defined. For this, the swarm begins in the deployment configuration but with modified OE of $\Omega = 22.5$° and $\omega = 45$°. Three maneuvers are performed by Spacecraft 1. First is a maneuver in the cross-track direction with magnitude 0.3 m/s at time $t = 5$ hours, to introduce out-of-plane relative motion. Second, a maneuver in the along-track direction with magnitude 0.2 m/s at time $t = 10$ hours, to introduce a difference in semi-major axis such that separation from targets increases over time. Third, a maneuver in the along-track direction with magnitude -0.2 m/s at time $t = 20$ hours, to remove the difference in semi-major axis and recover bounded relative...
The combined effect of these maneuvers is to recon-
figure into a science formation with larger target ranges of
orbits. The nominal satellite ballistic coefficient is
0.01, with ground truth values of ±20%. Target visibility and
visual magnitudes are computed using a model from Cognion
which takes into account the observer-target-Sun phase
angle, flux contributions from Mars albedo, and the variations
in reflected flux from different satellite surfaces. Clocks and
clock noise are propagated using the Galleani model with
includes both frequency and phase noise [45]. Clock quality
is based on the Microsemi SA.45s chipspan atomic clock
with an Allan deviation of $10^{-10}$ for $\tau = 1$ second [46].
Noise values of $q_1 = (3 \times 10^{-10})^2$ and $q_2 = (3 \times 10^{-14})^2$
are applied in the clock model. In simulations, the initial
differential clock drift between Spacecraft 1 and 4 is set as
1.5 seconds, with an initial differential drift rate of 1.5 µs/s.

Measurements are then synthesized from ground truth. The
DSN absolute orbit initialization uses a 1-σ error of 10m in
position and 10 mm/s in velocity [47]. Image measurements
for the local swarm observer are generated using 3D vector
graphics in OpenGL [48]. The visual magnitudes, angles, and
proper motions of stars are obtained from the Hipparcos star
catalog and any objects within the camera FOV are rendered
using Gaussian point spread functions. Noise is added to
the image attitude with 6° off-axis jitter and 30° boresight
jitter (1-σ). ISL measurements from remote observers are
computed using 1-σ bearing angle noise of (20°, 20°) and
attitude rotation angle noise of (6°, 6°, 30°). These values
are considered typical for modern CubeSat star trackers and
image centroiding algorithms [29] [41].

Simulations also include a CubeSat star tracker in the loop.
Input images for the observer are retrieved from a Blue
Canyon Technologies Nano Star Tracker as stimulated by
the Stanford SLAB Optical Stimulator (OS). The OS is a
variable-magnification testbed consisting of two lenses and
a microdisplay. Synthetic space scenes are generated and
shown on the display. By moving the two lenses and display
relative to each other, the VBS under test is stimulated with
appropriate magnification. The system is calibrated such that
the VBS image is similar in both radiosity and geometry to
what would be observed in orbit. Development, calibration
and usage of the OS is detailed by Beierle et al. in [48]
with achievable errors between desired and measured bearing
groups of less than 20°. Figure 13 presents the OS hardware.
Input measurements and telecommands are then sent to ARTMS for processing, which exists in a flight-code-like implementation in C++ and MATLAB Simulink. Simulations were run on a PC with an Intel i-7700HQ CPU and 16GB of RAM. The filter dynamics model uses a 20x20 GMM-3 gravity model without any other modelled perturbations. The filter integration timestep is 30s. In these simulations, covariance matching techniques and empirical acceleration estimation are not applied. The initial absolute orbit estimate and covariance are provided from the DSN measurement. The system’s initial clock drift and drift rate estimates are zero, with covariances of 1s and 100 µs/s respectively. No a-priori relative orbit information is provided. The BOD state initialization is set to occur after 4 hours, upon which SOD commences refinement of orbit estimates. Image measurements are received every two minutes.

**Simulation Results**

Navigation results for the science formation are presented in Figures 14 and 15. Plots display position and velocity errors in the RTN frame. Time $t = 0$ in each plot corresponds to the commencement of navigation by SOD. Despite significant measurement gaps, ARTMS is able to perform both absolute and relative orbit determination. Bearing angle measurements are used to maintain the absolute orbit initialization provided by the DSN and refine the relative orbit initialization computed by BOD. The absolute orbit is estimated to 900m position accuracy at steady state, and relative orbits are estimated to an accuracy of 0.5% of target range. The majority of position error occurs in the along-track direction, which remains the most challenging component to determine as it is analogous to the weakly observable target range. Other components of target motion are much more observable and see correspondingly smaller error. Differential clock drifts and clock drift rates are also effectively estimated. Despite large initial errors, drifts are estimated to within 0.02s and drift rates to within 0.4 µs/s. Convergence to steady state is achieved after approximately two orbits.

The state covariance does observe periodic growth and regression, partly due to eclipse periods during which measurements are unavailable, whereupon covariance steadily increases. This behavior is also influenced by orbit eccentricity. Near periapsis, velocities of the swarm are faster and there is more change in swarm states between measurements. Furthermore, swarm separations are larger, meaning that filter modelling is somewhat less accurate. This results in covariance growth near periapsis, and vice versa near apoapsis. Regular spikes of the relative orbit error are also observed near periapsis due to the larger impact of drag on swarm dynamics (which is not modelled by the filter). It is suggested that covariance matching techniques [20] or adaptive process noise estimation [36] could be applied to effectively treat this discrepancy without requiring additional dynamics models onboard. Large error spikes are also observed in the absolute orbit estimate, especially when exiting eclipse periods — the relatively simple onboard dynamics model leads to state propagation errors. However, these are quickly recovered, indicating good overall robustness of the system. In a similar vein, note that the initial absolute orbit error when SOD initializes is much larger than what is supplied by the DSN, because four hours of propagation are required to collect measurements for BOD (during which SOD is not receiving measurement updates).

Longer trials across a 200-hour time period, but without HIL measurements, display similar performance, indicating that convergence of the state estimate can be maintained indefinitely with angles-only measurements. It should be noted that clock drift estimation is necessary to achieve this: steady-state biases of approximately 2-3% in $\delta \lambda$ are observed per 0.1s of differential clock drift. Divergence of the absolute orbit estimate is also observed as drifts increase, due to increasing measurement errors. At periapsis where velocities are 3.5km/s, 0.1s of clock drift introduces roughly 350m of position error. Given that clock drift estimation is not significantly detrimental to observability, it is strongly recommended to estimate this on board.

Results for the deployment formation are presented in Figures 16 and 17. Despite 100% measurement availability throughout the orbit, performance is visibly degraded compared to the previous simulation. The absolute orbit is estimated to 1200m position accuracy at steady state, and relative orbits are estimated to a position accuracy of 0.5% of target range. Clock drifts are estimated to within 0.08s and convergence times for the relative state estimate are significantly longer. Larger error spikes are also observed in the relative state estimate near periapsis. As has been discussed previously, in-train formations are comparatively more challenging to track, because relative motion is small and $\delta \lambda$ is only weakly observable. Nevertheless, it is still possible to achieve absolute and relative orbit determination using angles-only measurements. Two aspects act to improve observability and make this possible: first, the eccentricity of the orbit introduces additional relative motion between targets, and second, the use of multiple swarm observers greatly aids robustness and convergence via stereo measurements.

Results for the swarm reconfiguration are presented in Figures 18 and 19. ARTMS is able to track the formation through maneuvers and successfully performs absolute and relative navigation. Maneuvers are provided to the architecture via telecommands but do possess ~5% magnitude errors. This leads to complications when estimating clock drifts. Immediately after a maneuver, the filter is unable to distinguish whether resultant error in target positions is due to an imprecise maneuver or an increase in clock drift. Sudden increases in clock estimation error are thus observed in the output. However, the filter is able to recover the clock drift estimate within two orbits.

It is also valuable to discuss the accuracy of the ARTMS autonomous initialization. In the above trials, during initialization, IMP achieves 100% measurement assignment precision and 85% measurement assignment recall for the science formation, and 98% precision and 64% recall for deployment. Lower recall is observed because in the deployment formation, targets are in close proximity in images, and IMP elects to make no assignment if the choice is considered.

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**Figure 13.** The SLAB Optical Stimulator.
ambiguous. This is, in part, to ensure high precision and avoid incorrect assignments since angles-only navigation is particularly sensitive to measurement errors. Using these measurements, BOD achieves initial position errors of (1.8, 4.3, 3.8, 3.8) km for Spacecraft 1 to 4 in the deployment formation, and (1.8, 3.6, 3.5, 3) km for the science formation. As expected, these results are somewhat worse than those in the observability analysis (which applied two orbits of measurements instead of one, and assumed perfect dynamics knowledge and better noise conditions). With the aid of subsequent measurements and the UKF, the system is able to move further towards the theoretical accuracy lower bound suggested by the observability analysis.

7. CONCLUSION

This research has presented an architecture to enable complete, autonomous navigation of spacecraft swarms in general
planetary orbit regimes, by using angles-only measurements obtained by onboard vision-based sensors. Key focuses of the architecture are distribution, and treatment of arbitrary swarm configurations consisting of multiple observers and multiple targets; autonomy, via self-contained navigation in deep space environments with minimal ground contact; and robustness, with long-term maneuver-free convergence and sufficient accuracy to enable proposed swarm missions under realistic measurement conditions. These goals are achieved by the use of a novel multi-observer framework and three core algorithms. First, an image processing algorithm applies multi-hypothesis tracking and parametric models of target kinematics to produce batches of bearing angles corresponding to known and unknown targets in the camera field of view, without a-priori target state information. Second, a batch orbit determination algorithm computes initial orbit estimates for the observer and its targets from bearing angle batches. The weakly-observable target range is estimated...
via sampling, and strongly-observable components are estimated using iterative batch least squares. Third, a sequential orbit determination algorithm continually refines the orbit estimates of the observer and its targets, using angle measurements from the local camera as well as remote observers, communicated over an inter-satellite link. An unscented Kalman filter is employed with a nonlinear dynamics model and an ROE state to resolve the weakly-observable range without requiring maneuvers. Multi-observer measurement assignment methods allow the filter to leverage distributed stereo measurements for vastly improved navigation performance. Clock drifts between swarm observers are also estimated on board. Together, these algorithms enable estimation of both absolute and relative swarm orbits with angles-only measurements, provided that each observer receives a coarse estimate of its absolute orbit at a single epoch. The architecture is particularly suited to miniaturized satellites as the only necessary hardware is a camera and low-bandwidth
radio link.

The achievable performance of multi-observer angles-only navigation was investigated with a numerical observability analysis and computation of the estimated state covariance. Results suggest that a minimum of three spacecraft is needed to enable observability of the complete swarm state, with at least two swarm observers. Observability is maintained for both in-train and E/I-vector separated formations in near-circular and eccentric orbits, though in-train formations are somewhat less observable. Given two orbits of measurements and representative sensor uncertainties, the following lower bounds are computed for estimation accuracy: 500m (absolute orbit), 0.2\% of target range (relative orbits) and 20 ms (relative clock offsets). This analysis is validated by high-fidelity camera-in-the-loop simulations of a proposed swarm science mission, consisting of four CubeSats in Mars orbit. Simulation results across different formation types demonstrate steady-state accuracies of <1 km in absolute position, <0.5\% of target range in relative position, and <0.1 s for clock offsets. Convergence of the state estimate is maintained during long-term testing, even in the presence of significant measurement gaps and orbit perturbations. However, periodic covariance growth and estimation errors were encountered due to higher velocities and larger swarm separations near periapsis, and the effects of unmodeled dynamics in the filter. It is suggested to treat this by adding adaptive process noise estimation. Clock drift estimation is also strongly recommended to prevent large multi-observer measurement errors and state errors. Viewed as a whole, simulations display promising navigation performance for a variety of swarm geometries, and the estimation accuracy is considered sufficient to enable the proposed science objective.

Future research avenues will involve more formal explorations of swarm formation design and communication/measurement topologies, and the impact of these elements on observability. Formalizing the links between swarm design and achievable navigation performance may offer insights into practical mission development. There is also potential to investigate algorithms for optimizing swarm observer attitudes, to ensure that targets remain maximally in view for consistent observation — this task may prove particularly challenging for certain swarm geometries, or if sensing is limited. Application to moon- or asteroid-orbiting missions and other dynamic environments will also be explored. Development of a flight code implementation of ARTMS is also continuing, as part of the Starling mission being developed by NASA Ames. Upcoming algorithmic additions for this mission include adaptive process noise estimation, automatic fault detection, and the ability for image processing to track maneuvering targets. Additionally, more extensive hardware-in-the-loop tests will be performed using CubeSat star trackers and flight processors for multi-spacecraft simulations. Flight testing of ARTMS in low Earth orbit is expected to occur aboard Starling in 2022.

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REFERENCES


Tracking Ideation Challenge.

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Simone D’Amico received the B.S. and M.S. degrees from Politecnico di Milano (2003) and the Ph.D. degree from Delft University of Technology (2010). From 2003 to 2014, he was research scientist and team leader at the German Aerospace Center (DLR). There, he gave key contributions to the design, development, and operations of spacecraft formation-flying and rendezvous missions such as GRACE (United States/Germany), TanDEM-X (Germany), PRISMA (Sweden/Germany/France), and PROBA-3 (ESA). Since 2014, he has been Assistant Professor of Aeronautics and Astronautics at Stanford University, Founding director of the Space Rendezvous Laboratory (SLAB), and Satellite Advisor of the Student Space Initiative (SSSI), Stanford’s largest undergraduate organization. He has over 150 scientific publications and 2500 google scholar’s citations, including conference proceedings, peer-reviewed journal articles, and book chapters. D’Amico’s research aims at enabling future miniature distributed space systems for unprecedented science and exploration. His efforts lie at the intersection of advanced astrodynamics, GN&C, and space system engineering to meet the tight requirements posed by these novel space architectures. The most recent mission concepts developed by Dr. D’Amico are a miniaturized distributed occulter/telescope (mDOT) system for direct imaging of exozodiacial dust and exoplanets and the Autonomous Nanosatellite Swarming (ANS) mission for characterization of small celestial bodies. D’Amico’s research is supported by NASA, NSF, AFRL, AFOSR, KACST, and Industry. He is Chairman of the NASA’s Starshade Science and Technology Working Group (TSWG). He is member of the advisory board of space startup companies and VC edge funds. He is member of the Space-Flight Mechanics Technical Committee of the AAS, Associate Fellow of AIAA, Associate Editor of the AIAA Journal of Guidance, Control, and Dynamics and the IEEE Transactions of Aerospace and Electronic Systems. He is Fellow of the NAE’s US FOE Symposium. Dr. D’Amico was recipient of the Leonardo 500 Award by the Leonardo Da Vinci Society and ISSNAF (2019), the Stanford’s Introductory Seminar Excellence Award (2019 and 2020), the FAINA’s Group Diploma of Honor (2018), the Exemplary System Engineering Doctoral Dissertation Award by the International Honor Society for Systems Engineering OAA (2016), the DLR’s Sabbatical/Forschungssemester in honor of scientific achievements (2012), the DLR’s Wissenschaft Preis in honor of scientific achievements (2006), and the NASA’s Group Achievement Award for the Gravity Recovery and Climate Experiment, GRACE (2004).