Article

Mapping and determining the center of mass of a rotating object using a moving observer

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Abstract

For certain applications, such as on-orbit inspection of orbital debris, defunct satellites, and natural objects, it is necessary to obtain a map of a rotating object from a moving observer, as well to estimate the object’s center of mass. This paper addresses these tasks using an observer that measures its own orientation, angular rate, and acceleration, and is equipped with a dense 3D visual sensor, such as a stereo camera or a light detection and ranging (LiDAR) sensor. The observer’s trajectory is estimated independently of the target object’s rotational motion. Pose-graph mapping is performed using visual odometry to estimate the observer’s trajectory in an arbitrary target-fixed frame. In addition to applying pose constraint factors between successive frames, loop closure is performed between temporally non-adjacent frames. A kinematic constraint on the target-fixed frame, resulting from the rigidity of the target object, is exploited to create a novel rotation kinematic factor. This factor connects a trajectory estimation factor graph with the mapping pose graph, and facilitates estimation of the target’s center of mass. Map creation is performed by transforming detected feature points into the target-fixed frame, centered at the estimated center of mass. Analysis of the algorithm’s computational performance reveals that its computational cost is negligible compared with that of the requisite image processing.

Keywords

SLAM, dynamic, rotation kinematic factor

1. Introduction

Many objects in space, such as orbital debris, defunct satellites, and natural objects, are uncooperative and unknown, meaning that they are not equipped with working sensors or actuators, and may have unknown visual appearance and inertial properties. There are several reasons to want to visit these uncooperative space objects with an observer satellite (a.k.a. an inspector): to deorbit or deflect dangerous debris; to inspect or repair defunct satellites; or to observe, sample, or extract resources from natural objects, such as asteroids and comets. After making an orbital rendezvous with the object (a.k.a. the target), a mission designed to accomplish one of the aforementioned objectives will typically involve observing the target object from a safe distance, acquiring information, and planning the subsequent phases of the mission.

To approach and dock to the target, subsequent phases of the mission will require a 3D map for relative pose determination. The target’s center of mass will also be required to predict, in conjunction with a motion model, the future location of a docking or grasping location on the target. Existing algorithms for mapping an unknown target have assumed that either the target or the inspector is stationary (Augenstein, 2011; Lichter, 2005; Tweddle, 2013). However, in realistic cases, both the inspector and the target are moving with similar time constants, and maneuvering of the inspector to obtain new vantage points is both expected and desired. Therefore, existing techniques require fundamental extension.

Lichter (2005) obtains 3D point clouds from a team of static inspectors surrounding an unknown tumbling object. These data allow his algorithm to quickly build an occupancy-grid-based map and calculate the object’s geometric center. The stationary sensor array subsequently provides measurements of both the orientation and translation of the geometric frame. An unscented Kalman filter is used

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to recursively estimate the target’s geometric frame orientation, inertial angular velocity, a quaternion parameterization of inertia ratios, and rotation from the true principal axes to the principal geometric axes. A linear Kalman filter is used in parallel for estimation of the translation variables.

Hillenbrand and Lampariello (2005) use simulated range data from a stationary inspector to perform open-loop visual odometry with respect to a passive target, which is both rotating and translating. An estimate of the target’s center of mass is obtained in a least-squares manner using the visual odometry motion estimates. Although a map is not explicitly presented, the authors suggest that the results could be used to make a geometric model of the target.

Augenstein (2011) estimates the orientation, angular velocity, translation to, and map of a tumbling target with a monocular camera using a hybrid Bayesian estimation and particle filter approach. Although allowing for a moving target, he assumes that the position of the inspector is known at the time of acquisition of all images. For rotational motion, he uses simplified versions of Euler’s equations to predict feature positions resulting from pure rotation for several hypothetical states (particles in a particle filter).

Aghili et al. (2011) and Aghili and Su (2016) use a LiDAR sensor to obtain a point cloud from a known but tumbling target. An iterative closest point is used to match the point cloud to a 3D CAD model of the target to determine the relative pose from camera to target. In full, the extended Kalman filter estimates the relative position, velocity, and orientation of the target relative to the inspector, and the body angular velocities, ratios of inertia, principal axes of inertia, and position of the center of mass of the target. Aghili et al. incorporate relative motion of the inspector with respect to the target, driven by orbital mechanics and thrusting; however, their framework has not been applied to targets with unknown 3D structures.

Tweddle (2013) uses a stereo vision system to obtain sparse 3D landmarks of a tumbling target satellite. The inspector satellite is considered inertially static, and a factor graph formulation is used to solve a simultaneous location and mapping (SLAM) problem with inverted dynamics (i.e., static camera and moving scene). Variable nodes in the factor graph are created for the state of the target at each time of acquisition of all images. For rotational motion, the exponential and logarithmic singularity, they are commonly used for representing uncertainty and performing optimization near the identity rotation. For these applications, the exponential and logarithmic maps can be used to map from angle-axis vectors \( \theta \) to rotation matrices \( \mathbf{R} \) (so(3) \( \Rightarrow \) SO(3)) or rotation matrices \( \mathbf{R} \) to angle-axis vectors \( \theta \) (SO(3) \( \Rightarrow \) so(3)), respectively, where

\[
\mathbf{C}_A \mathbf{R} = \mathbf{b} \mathbf{R} \mathbf{g} \mathbf{R}^{-1}
\]

(1)

Angle-axis vectors \( \theta = \theta \mathbf{a} \) represent both the magnitude and direction of the rotation, where \( \theta \) is the angle of rotation, and \( \mathbf{a} \) is the unit vector along the axis of rotation. The \( ^\wedge \) operator creates a skew-symmetric matrix from an angle-axis vector, whereas the \( ^\vee \) operator performs the reverse operation

\[
\theta^\wedge = \left[ \begin{array}{ccc}
0 & -\theta_3 & \theta_2 \\
\theta_3 & 0 & -\theta_1 \\
-\theta_2 & \theta_1 & 0
\end{array} \right], \quad \left[ \begin{array}{ccc}
0 & -\theta_3 & \theta_2 \\
\theta_3 & 0 & -\theta_1 \\
-\theta_2 & \theta_1 & 0
\end{array} \right]^{\vee} = \theta
\]

(2)

The \( ^\wedge \) operator has the following useful properties

\[
\theta^\wedge \mathbf{t} = \theta \times \mathbf{t} = -\mathbf{t} \times \theta = -\theta^\wedge, \quad (\theta^\wedge)^T = -\theta^\wedge
\]

(3)

Rotation in three dimensions exists on a manifold called the rotation group SO(3) and has three degrees of freedom. Although three parameter representations always contain a singularity, they are commonly used for representing uncertainty and performing optimization near the identity rotation. For these applications, the exponential and logarithmic maps can be used to map from angle-axis vectors \( \theta \) to rotation matrices \( \mathbf{R} \) (so(3) \( \Rightarrow \) SO(3)) or rotation matrices \( \mathbf{R} \) to angle-axis vectors \( \theta \) (SO(3) \( \Rightarrow \) so(3)), respectively, where
so(3) is a subspace of \( R^3 \) inside the sphere of radius \( \pi \) (i.e., \( \theta \in R^3, \| \theta \| < \pi \)). The exponential map is given as

\[
R = \text{Exp} (\theta) = \exp (\theta^\wedge) \\
= I_3 + \frac{\sin (\theta)}{\theta} \theta^\wedge + \frac{1 - \cos (\theta)}{\theta^2} (\theta^\wedge)^2 \\
\approx I_3 + \theta^\wedge
\]

where \( \text{Exp} (\theta) \) is used herein as a short-form notation for the matrix exponential of a skew-symmetric matrix \( \exp (\theta^\wedge) \), and the linearization is given by \( I_3 + \theta^\wedge \). Useful properties for algebraic manipulation of the exponential map are given below (Forster et al., 2015)

\[
R \text{Exp} (\theta) = \text{Exp} (R \theta) R \\
\text{Exp} (\theta) R = R \text{Exp} (R^T \theta)
\]

The logarithmic map is given as

\[
\theta = \text{Log} (R) = \log (R^\vee) = \frac{\theta}{2 \sin (\theta)} (R - R^T)^\vee \\
\theta = \arccos \left( \frac{\text{tr} (R) - 1}{2} \right)
\]

where \( \text{Log} (R) \) is used herein as a short-form notation for the angle-axis vector from matrix logarithm \( \log (R)^\vee \).

Small angle-axis vectors \( \delta\theta \in \text{so}(3) \) can be used to perturb the rotation. These vectors \( \delta\theta \) can be sampled from a Gaussian distribution to represent uncertainty in rotation with respect to the mean value \( \bar{R} \)

\[
R = \bar{R} \text{Exp} (\delta\theta), \quad \delta\theta = \text{Log} (\bar{R}^T R)
\]

\[
\delta\theta \sim N (0_{3 \times 1}, \Sigma_R)
\]

2.2. Pose

The pose of coordinate frame \( B \) refers to the combination of its rotation and translation with respect to another coordinate frame \( A \). It can be compactly represented by a \( 4 \times 4 \) pose matrix \( A_P \)

\[
A_P = \begin{bmatrix}
P_{01} & 0_{1 \times 3} & 1 \\
0_{1 \times 3} & I_3 & T_{b0}
\end{bmatrix}
\]

Poses can be inverted, as

\[
B_P = A_P^{-1} = \begin{bmatrix}
A_P^T & -A_P^T T_{b0} & 0_{1 \times 3}
0_{1 \times 3} & I_3 & 1
\end{bmatrix}
\]

Poses are composed in the opposite order to rotation matrices

\[
C_P = B_P A_P
\]

Small vectors \( \delta P = [\delta\theta^T \delta t]^T \) can be used to perturb the pose. Here, the first three terms of the vector \( \delta P \) are the angle-axis perturbation \( \delta\theta \) as in equation (9), and the final three terms of the vector are the translation perturbation \( \delta t \)

\[
B_P = A_P \delta P = \begin{bmatrix}
A_P^T & -A_P^T T_{b0} & 0_{1 \times 3}
0_{1 \times 3} & I_3 & 1
\end{bmatrix}
\begin{bmatrix}
\text{Exp} (\delta\theta) & \delta t \\
0_{1 \times 3} & 1
\end{bmatrix}
\]

\[
\delta P = [\delta\theta^T \delta t]^T \sim N (0_{6 \times 1}, \Sigma_P)
\]

2.3. Smoothing-based estimation

Smoothing-based estimation is a batch method, which attempts to find the maximum a-posteriori estimate of a set of random variables \( \Theta \). This is accomplished by finding optimal values \( \Theta^* \) that maximize the joint probability of \( \Theta \) and noisy measurements \( Z \). In some instances, a set of commanded control inputs \( U \) is also included to parameterize the problem; herein these control inputs are treated as random variables with low covariance. Thus, the smoothing-based estimation problem can be defined as finding the optimal vector \( \Theta^* \), as

\[
\Theta^* = \arg \max_\Theta P (\Theta, Z, U) \\
= \arg \max_\Theta P (Z, U | \Theta) P (\Theta)
\]

Assuming that each measurement is Gaussian, and using the monotonic natural logarithm function, this problem can
be reduced to the problem of minimizing the sum of several probabilistic factors (Kaess et al., 2012)

\[
\Theta^* = \arg \min_{\Theta} - \log(P(Z, U | \Theta) P(\Theta))
\]

\[
= \arg \min_{\Theta} \frac{1}{2} \sum_k \| z_k - h(\theta_k) \|^2_{\Sigma_k}
\]

where \( z_k \) is the measurement value, \( h(\theta_k) \) denotes the measurement model as a function of a subset of \( \Theta \), and \( \Sigma_k \) is the measurement’s covariance.

Using this framework, several Gaussian measurements can be incorporated, so long as there exists a measurement model \( h \) in terms of the variables \( \Theta \) and an estimate of the measurement covariance \( \Sigma_k \). Gaussian prior belief can also be incorporated using the simple measurement model \( h(\theta_k) = \theta_k \). For real-world problems, the resultant optimization problem is typically a large, nonlinear, non-convex problem. The state-of-the-art incremental smoothing and mapping technique (iSAM2) exploits the structure and sparsity of the problem to obtain efficient solutions that can commonly be computed in real time (Kaess et al., 2012). The open source GTSAM software (Dellaert et al., 2012), which implements iSAM2, is used for smoothing-based estimation in this paper.

3. Review of trajectory estimation

This section reviews the trajectory estimation technique presented in Setterfield et al. (2017), which is used herein to determine the trajectory of the inspector satellite in a manner that is independent of the target’s rotational motion.

An overview of the requisite coordinate frames is given in Figure 2. The inspector’s body frame \( B \) is located at its center of mass, and aligned with its principal axes of inertia; calibrated gyroscopes measure the angular velocity in this frame. The pose of \( B \) is estimated with respect to the world navigation frame \( W \); the frame \( W \) is a target-centered inertial coordinate frame, meaning that its origin is attached to the center of mass of the target, but it is rotationally inert (i.e., fixed with respect to the stars). The camera frame \( C \) is located at a known position and orientation on the inspector. The target body frame \( T \) is attached to its center of mass and aligned with its principal axes.

Using the technique from Setterfield et al. (2017), the maximum a-posteriori estimate for the full six-degrees-of-freedom (6-DOF) trajectory of the inspector satellite is estimated. Specifically, this involves solving for the most probable navigation state vector \( x \) over a sequence of time steps \( I = \{0, 1, \ldots, h, \ldots, i, j, \ldots, N\} \)

\[
x_I = \{\mathbb{R}^6, \mathbb{R}^6_{\text{vel}}, \mathbb{R}^6_{\text{pos}}, \mathbb{R}^6, \mathbb{R}^6\}_{I}
\]

\[
x \in \{SO(3), \mathbb{R}^3, \mathbb{R}^3, \mathbb{R}^3, \mathbb{R}^3, \mathbb{R}^3\}
\]

where \( \mathbb{R}^6 \) is the orientation of the inspector body frame \( B \) in the world frame \( W \), \( \mathbb{R}^6_{\text{vel}} \) is the position of the inspector center of mass in the world frame, \( \mathbb{R}^6_{\text{pos}} \) is the velocity of the inspector center of mass in the world frame, \( \mathbb{R}^6 \) is the gyroscopic bias, and \( \mathbb{R}^6 \) is the acceleration bias.

Measurements of range \( Z^r = \| t_{\text{ColW}} \|_W \) and bearing \( Z^b = \{t_{\text{ColW}}/\| t_{\text{ColW}} \|_W \} \) from the inspector to the target’s approximate centroid are obtained using an averaged depth map from radar, LiDAR, or a stereo camera. Measurements of orientation \( Z^o = \mathbb{R}^6_T \) of the inspector in the inertial frame are provided by a star tracker. High frequency measurements of angular rate \( Z^\omega = \{z^\omega_{b_{1,1}}, z^\omega_{b_{2,2}}, \ldots, z^\omega_{b_{N-1,N}}\}\) (where \( z^\omega_{ij} = \{\theta_{b_{1,1}}, \theta_{b_{2,2}}, \ldots, \theta_{b_{N-1,N}}\}\)) are collected between time steps in \( I \) using a three-axis gyroscope. Similarly, high frequency acceleration “measurements” \( Z^a = \{\mathbb{R}^6_{a_{1,1}}, \mathbb{R}^6_{a_{2,2}}, \ldots, \mathbb{R}^6_{a_{N-1,N}}\}\) (where \( \mathbb{R}^6_{a_{ij}} = \{\mathbf{u}_{i,j}^1, \mathbf{u}_{i,j}^2, \ldots, \mathbf{u}_{i,j}^m\}/m\) are obtained by dividing the commanded forces \( \mathbf{u} \) by the spacecraft mass \( m \). Although not performed herein, accelerations from relative orbital dynamics from the Clohessy–Wiltshire equations can be incorporated into these acceleration “measurements”.

An overview of the requisite measurements is shown in Figure 2. To determine the full 6-DOF trajectory of the inspector satellite, a smoothing-based estimation approach of the type in equation (17) is adopted, as represented by the factor graph in Figure 3(a). A prior factor \( \phi_{\psi_0} \) with a very low covariance is placed on the position of the origin of \( W \) to enforce its location at the origin, or elsewhere if convenient. A prior belief on initial state is obtained from the long-range estimation scheme and applied as a prior factor \( \phi_{\psi_0} \). Range and bearing measurements of the target’s geometric centroid from the inspector are considered approximate range and bearing measurements to the origin of \( B \), and input into the problem as range and bearing factors \( \rho \). Star tracker measurements are applied as partial unary factors \( \sigma \) to the orientation component \( \mathbb{R}^6_T \) of the inspector’s state. Measurements of angular rate and acceleration are applied using preintegrated inertial odometry factors \( \psi \), described in Forster et al. (2015). It is assumed that orientation and range and bearing measurements arrive at a lower frequency than angular rate and acceleration measurements.
Observability of the state can be seen intuitively, given the measurements. The range measurement from the inspector to the target restricts the location of the inspector to a sphere around the target. The star tracker measurement of orientation then restricts the three rotational degrees of freedom of the inspector. The remaining two degrees of freedom are restricted by the bearing measurement to the target, which places the inspector satellite at a specific point on the sphere. The observability of velocity follows from the time rate of change of position, and the observability of gyroscope and acceleration biases follows from the accurate knowledge of orientation and the observability of velocity, respectively.

4. Mapping

The objective of this section is to create a 3D map of the target, comprising visual feature points capable of being re-detected in subsequent phases of the mission. To accomplish this, visual odometry is first performed to determine the motion of the inspector satellite relative to the target object. The maximum a-posteriori pose graph for relative motion is then developed using smoothing-based estimation techniques. This allows a map of the target object to be created by reprojecting visual measurements into a target-fixed coordinate frame.

4.1. Required measurements and coordinate frames

To perform pose-graph-based mapping of the target object, a set of camera measurements $Z_i$ over a sequence of time steps $T$ is required. Herein, camera measurements $Z_i$ are 3D locations of visual feature points of interest with an attached descriptor; the descriptor associated with each point allows the same feature point to be re-detected in other images.

The coordinate frames used in this section are identical to those introduced in Section 3, with the addition of the geometric frame $G_i$. This frame, shown in Figure 2, is fixed to the target object. By convention, its orientation is aligned with the inspector’s body frame $B$ at the instant when the first image is taken (i.e., $G_{0}B_{0}R = I_3$), and its origin is at the center of all inlying visual features from the first image. Inlying features are those that both match features in the second image and contribute to the visual odometry solution (see Section 4.2).

4.2. Visual odometry

To form a pose graph, it is desired that the pose change of the camera frame $C$ between two time steps $i$ and $j = i + 1$ be estimated with reference to the target-fixed geometric frame $G_i = G_j \forall i, j \in T$. This is equivalent to treating the target object (and consequently the geometric frame $G_i$) as “static” for this section, so that conventional visual odometry can be performed. The 3D image data acquired at time steps $i$ and $j$ must contain overlapping parts of the scene to facilitate motion estimation.

When performing visual odometry, the choice of algorithm depends largely on the sensor being used. Herein, the discussion is limited to 3D sensors, such as stereo cameras, LiDAR, time of flight cameras, etc., although visual odometry has also been demonstrated using monocular cameras (Davison et al., 2007; Engel et al., 2014). When LiDAR or time of flight cameras are used, a dense 3D point cloud of the scene is obtained. In the case where this 3D scan...
is not accompanied by an image, an iterative-closest-point type method can be used to solve for the relative motion between frames (Besl and McKay, 1992). The work herein uses images from a stereo camera, so a feature-based visual odometry technique will be discussed in detail. When two stereo images of the same scene are taken, points of interest can be extracted and matched between all four individual images: that is, left and right images in frame \( C_i \) and left and right images in frame \( C_j \). Left-to-right feature correspondences will have image coordinates \((u_L, v_L)\) and \((u_R, v_R)\) in the left and right images, respectively. Correspondences that have similar vertical coordinates (i.e., satisfy the epipolar constraint \( v_L \approx v_R \)) are triangulated to get three-dimensional points. The coordinates on the image plane can be summarized by stereo coordinates \( s \); from this, the 3D location of the point in the left camera’s frame \( C \) \( C_i t_p \) is given as follows (see Figure 4(a))

\[
s = \begin{bmatrix} u_L \\ u_R \\ v_L \\ v_R \end{bmatrix}, \quad C_i t_p = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} t_x (u_L - c_{Lx}) \\ \frac{u_L - c_{Lx}}{f} \\ t_y (v_L - c_{Ly}) \\ \frac{v_L - c_{Ly}}{f} \end{bmatrix}
\] (19)

where \((x, y, z)\) are the coordinates of the point with respect to the left camera’s focal point, the z-axis is the optical axis, \( t_c \) is the stereo camera baseline, \( f \) is the camera’s focal length, \( (c_{Lx}, c_{Ly}) \) are the image coordinates of the left image’s optical center, and the image has been rectified so that the left and right images have the same focus and center (i.e., \( f_R = f_L = f, c_{Rx} = c_{Lx} \), and \( c_{Ry} = c_{Ly} \)).

These successfully triangulated points are then matched from frame to frame to facilitate motion estimation. Herein, motion estimation is derived as if the scene remains static, and the stereo camera frame moves from frame \( C_i \) to frame \( C_j \). The rotation \( C_i^T R \) and translation \( C_i t_{C_i(toc_j)} \) of the stereo camera that best represent the camera motion in three dimensions are sought. A measured point in frame \( C_i, C_i t_p \), can be transformed into frame \( C_j \), creating a prediction \( C_j t_{p}^{\epsilon} \) of the position of the corresponding measured point in frame \( C_j, C_j t_p \)

\[
C_j t_{p} = C_j^T (C_i t_p - C_i t_{C_i(toc_j)})
\]

(20)

The error in prediction of this point \( \epsilon \) can be found by comparing the predicted point position \( C_J t_{p}^{\epsilon} \) with the corresponding measured point position \( C_j t_p \)

\[
\epsilon = C_j t_p - C_j t_{p}^{\epsilon} = C_j t_p - (C_j^T C_i R C_i t_p - C_j t_{C_i(toc_j)})
\]

(21)

In this paper, the following problem is solved twice, in a similar manner to as on the Mars Exploration Rovers (Maimone et al., 2007).

\[
\begin{bmatrix} C_i^T R \mid C_i t_{C_i(toc_j)} \end{bmatrix} = \arg\min_{c_i^T R, C_i t_{C_i(toc_j)}} \sum_{l=1}^{M} \| \epsilon_l \|^2_{\Sigma_{\epsilon_l}} \quad \epsilon_l \sim \mathcal{N}(0_{3 \times 1}, \Sigma_{\epsilon_l})
\] (22)

Firstly, the problem is solved with \( \Sigma_{\epsilon_l} = I_3 \), using the closed form solution of absolute orientation from Horn (1987) wrapped with Random Sampling and Consensus (RANSAC) (Fischler and Bolles, 1981). This step determines the largest subset of inlying features that passes a “rigidity check” and provides a least-squares estimate of \( \{C_i^T R, C_i t_{C_i(toc_j)}\} \) that is not weighted by feature position uncertainty (see Figure 4(b)).

Secondly, a maximum-likelihood estimate is obtained using the method from Matthies (1989), where \( \Sigma_{\epsilon_i} \) is the covariance of each feature’s error \( \epsilon \). In stereo vision, points close to the camera tend to have less error than those that are far away; this formulation properly accounts for their relative uncertainty (see Figure 4(c)). The maximum-likelihood estimator is initialized with the rotation, the translation, and the \( M = M_{in} \) inlying points found in the least-squares step. The final result of the visual odometry algorithm is the relative camera pose \( \{C_i^T P_i\}_G \) from frame \( C_i \) to frame \( C_j \) together with an associated uncertainty \( \Sigma_{P_C} \) (Setterfield, 2017a).

\[
\left[ C_i^T P_i \right]_G = \left[ C_i^T R \right]_G \left[ C_i^T t_{C_i(toc_j)} \right]_G
\]

(24)

\[
P \left( \left[ C_i^T P_i \right]_G \mid \left[ z_{C_i}, z_{C_j} \right] \right) \sim \mathcal{N} \left( \left[ C_i^T P_i \right]_G, \Sigma_{P_C} \right)
\]

(25)

\[
\Sigma_{P_C} = E \left[ \left[ \delta t_c^T \delta t_c^T \right] \right]
\]

(26)
where $\delta \theta_C$ is the so(3) rotation uncertainty, and $\delta t_C$ is the $\mathbb{R}^3$ translation uncertainty. The $G$ subscript on pose change $\{G\}_C$ emphasizes the fact that frame $G$ is considered the static reference for the relative camera poses.

Visual odometry is illustrated in Figure 5. With $G$ established as a static reference, a conventional visual pose-graph approach is pursued. Frame-to-frame feature descriptor matching is attempted between each new image and the previous image as well as each new image with a randomly selected previous image (loop closure). Loop closures improve the quality of the map by preventing drift caused by compounding errors in visual odometry.

### 4.3. Smoothing-based mapping

In this section, the time history of inspector body poses in the geometric frame (i.e., $B_T$ for a series of time steps $I$) is estimated.

#### 4.3.1. Pose-graph initialization

Based on the definition of coordinate frame $G$ in Section 4.1, the initial pose of the inspector in the target geometric frame $G$ is determined as

$$
B_0 = \begin{bmatrix}
1_I & 0_{1 \times 3} \\
0_{1 \times 3} & 1
\end{bmatrix}
$$

(27)

where $B_0$ is the known rotation from camera frame $C$ to inspector body frame $B$.

4.3.2. Pose changes in the inspector body frame. Herein, the pose of the inspector body frame $B$ (as opposed to the camera frame $C$) is tracked. All camera pose changes $\{C\}_G$ from visual odometry are transformed into measurements of inspector body pose changes $\{B\}_G$ using the known transformation $\{C\}_G B$

$$
\begin{bmatrix}
B_j \mid B_i \end{bmatrix}_G \Rightarrow \begin{bmatrix}
B_j \mid B_i \end{bmatrix}_G = \begin{bmatrix}
B_j \mid B_i \end{bmatrix}_G C^{-1} \quad (29)
$$

The covariance $\Sigma_{B_G}$ must also be transformed into covariance in $\{B\}_G$, denoted $\Sigma_{B_CB}$, as outlined in Setterfield (2017a).

4.3.3. Pose prior factor. A prior Gaussian belief $z^0 = B_0$ with the value given in equation (27) is applied directly to the initial pose. A low covariance $\Sigma_p$ is used to enforce the initialization convention. The prior belief $z^0$ has a rotation component $z^0 = \log B_0$ and a translation component $z^0 = \log t_{G_0 to B_0}$, and is applied using the prior factor $\phi_{B_G}$

$$
P \left( \theta_k = \log B_0 \mid \log B_0 \right) \sim N \left( \theta_k \mid \Sigma_{B_0} \right) \quad (30)
$$

$$
\phi_{B_G} = \left[ \left[ \log B_0 R^T \log z^0 \right] \right]^2 \Sigma_{B_0}
$$

4.3.4. Pose constraint factor. The motion measurement $z^m = \{B\}_G$ has a rotation component $z^m = \{B\}_G R$ and a translation component $z^m = \{B\}_G t_{G_0 to B_0}$ and is applied as a vision factor $v$

$$
P \left( \theta_k = \log B_0 \mid \log B_0 \right) \sim N \left( \theta_k \mid \Sigma_{B_0} \right) \quad (31)
$$

$$
v = \left[ \left[ \log B_0 R^T \log z^m \right] \right]^2 \Sigma_{B_0}
$$

where $\Delta t_{G_0 B_0} = \log t_{G_0 to B_0} - \log t_{G_0 to B_0}$.

4.3.5. Mapping pose graph. The problem of estimating the maximum a-posteriori time series of inspector poses in the target object’s geometric frame $B_T$ is formulated as a batch optimization problem of the type described in equation (17). The joint probability distribution of all poses $\theta$ and measurements $Z$ is represented by the factor graph depicted in Figure 3(b); note that without the central factors this graph is completely separate from the trajectory factor graph.

### 5. Estimation of the target’s center of mass

In this section, pose estimates of the inspector body frame $B$ with reference to the world frame $W$ from Section 3 are considered, together with pose estimates of the inspector body.
frame $B$ with reference to the target-fixed frame $G$ from Section 4, in order to determine the center of mass of the target object. Firstly, pose estimates for the target object’s body-fixed geometric frame $G$ are calculated with reference to the world frame $W$ at each time step $i \in \mathcal{I}$

$$
\frac{G}{W} \mathbf{P} = \frac{B}{G} \mathbf{P} \frac{B}{G}^{-1}
$$

(32)

Since the target object is assumed to be a rigid body that undergoes only rotational motion, the motion of the target-fixed geometric frame $G$ is constrained by its kinematics. Recalling that the target’s body frame $B$ is situated at its center of mass, the translation from the geometric frame to body frame $G_{\text{frame}}$ is constant. Using the summation of vectors illustrated in Figure 6, a rotational kinematic constraint $\epsilon_k \approx \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$ is constructed between temporally adjacent time steps $i$ and $j = i + 1$

$$
0_{3 \times 1} \approx \epsilon_{k} = -t_{G_{\text{body}}} + t_{G_{\text{body}}} - t_{G_{\text{body}}} + t_{G_{\text{body}}} \cdots
$$

(33)

Rotating all translations into the world frame $W$, using $t_{G_{\text{body}}} = t_{W_{\text{body}}} - t_{W_{\text{body}}}$, and recognizing that for the rigid target object $\frac{G}{W} t_{G_{\text{body}}} = \frac{G}{W} t_{G_{\text{body}}} = \frac{G}{W} t_{G_{\text{body}}}$, the constraint $\epsilon$ can be rewritten as

$$
\epsilon_k = \frac{W}{B} R \frac{B}{G} \mathbf{R} \left( \frac{G}{W} t_{G_{\text{body}}} - \frac{G}{W} t_{G_{\text{body}}} \right) \cdots
$$

(34)

The rotational kinematic constraint created here can be used to solve for the target’s center of mass in a linear, least-squares manner (Section 5.1), or in a weighted least-squares manner, as part of a factor graph (Section 5.2).

5.1. Linear solution

A linear least-squares solution for the center of mass can be obtained by rearranging equation (34) into the form

$$
A_i \frac{G}{G_{\text{frame}}} = b_i
$$

(35)

These equations can be stacked and the optimal translation of inspector position in the world frame can be solved for in a linear least-squares sense

$$
\frac{G}{G_{\text{frame}}} = \arg \min_{\frac{G}{G_{\text{frame}}}} \left\| A \frac{G}{G_{\text{frame}}} - b \right\|^2
$$

$$
= (A^T A)^{-1} A^T b
$$

(37)

Note that this problem is poorly conditioned (i.e., has a high condition number) along the target’s axis of rotation when the axis of rotation remains constant or nearly constant over the time steps $\mathcal{I}$. This occurs for datasets over short time intervals, or for scenarios in which the target object is undergoing single-axis rotation. When the condition number is high, the rotation axis can be identified, but the specific point on the rotation axis that coincides with the center of mass is unobservable.

5.2. Rotation kinematic factor

The rotational kinematic constraint defined in equation (34) can be used to create a probabilistic rotation kinematic factor. Deviations in the value of $\epsilon_k$ from $0_{3 \times 1}$ can come from two sources. The first is actual translation of the center of mass $B$ of the target object between time steps $i$ and $j = i + 1$. Since the world frame $W$ is attached to the target’s center of mass $B$, and the relative orbital dynamics between the inspector and the target are assumed to be well modeled, this translation could only come from external forces, such as solar pressure, air drag, micrometeoroid impact, or unbalanced application of thruster forces. The second potential source of deviation is variation in the measured range and bearing to the target’s centroid. In equation (34), the term $(\frac{W}{B} t_{W_{\text{body}}} - \frac{W}{B} t_{W_{\text{body}}})$ relies on the estimates of inspector position in the world frame $W$, which rely on range and bearing measurements to the target’s visual centroid (see Section 3). As the vantage point of the camera changes, it is also possible that the target’s perceived visual centroid moves in inertial space. This motion may or may not reflect actual relative motion, but will cause errors in $\epsilon_k$. Since time steps $i$ and $j$ are temporally adjacent, this
“vantage point” error is small in magnitude. Inspector navigation states \( x \) are also attached by an inertial odometry factor (described in Section 3) which provides an independent measure of the inspector’s motion; this factor will also minimize the effect of “vantage point” error.

The rotational kinematic constraint \( \epsilon^* = \epsilon_{\chi \epsilon} = \mathbf{0}_{3 \times 1} \) is applied as a Gaussian belief with covariance \( \Sigma_{\epsilon} \). The value of \( \Sigma_{\epsilon} \) can be set and estimated a priori, based on simulations of the expected shape of the target object and properties of the visual sensor. Alternatively, the least-squares solution from Section 5.1 can be obtained, and the variance of the residuals of \( \epsilon_{\chi \epsilon} \) can be used to determine the order of magnitude of \( \Sigma_{\epsilon} \). Note that since errors \( \epsilon_{\chi \epsilon} \) are equally likely in any direction and are uncorrelated between directions, \( \Sigma_{\epsilon} \) is diagonal. The novel rotation kinematic factor \( \kappa \) can then be defined as

\[
P ( \epsilon^* | \theta_k ) \sim N ( \epsilon_{\chi \epsilon} ) \quad \theta_k = \frac{\| \epsilon_{\chi \epsilon} \|^2}{\Sigma_{\epsilon}}
\]

(38)

To perform efficient nonlinear estimation using the GTSAM 4.0 open source smoothing and mapping software library used in this paper, the Jacobians of the error term \( \epsilon_{\chi \epsilon} \) with respect to each of the five variables in \( \theta_k \) are required. Note that Jacobians of pose variables consist of side-by-side Jacobians with respect to rotation and translation (i.e., \( \mathbf{H}_p = [\mathbf{H}_R \ \mathbf{H}_t] \)). For these derivations, it is helpful to define the terms \( \chi_i \) and \( \chi_j \)

\[
\chi_i = \frac{w_i}{b_i} \frac{b_j}{b_i} R \left( G_i t_{\omega_0 b_i} - G_i t_{G_0 G_0 b_i} \right)
\]

(39)

\[
\chi_j = \frac{w_i}{b_i} \frac{b_j}{b_i} R \left( G_i t_{G_0 G_0 b_i} - G_i t_{\omega_0 b_i} \right)
\]

(40)

First, consider the Jacobian of \( \epsilon_{\chi \epsilon} \) with respect to the rotational component of \( \frac{w_i}{b_i} \mathbf{P} \). Jacobians with respect to rotation in \( \text{SO}(3) \) are taken by perturbing the rotation by a small angle-axis rotation vector \( \varphi \), as in equation (15), and then taking the first derivative with respect to the perturbation. The properties of the \(^\wedge\) operator from equation (3) and the adjoint property of rotation from equation (5) are used below

\[
\mathbf{H}_{1} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial R} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \varphi}
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \frac{w_i}{b_i} R \left( G_i t_{\omega_0 b_i} - G_i t_{G_0 G_0 b_i} \right) \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \mathbf{I}_i + \left( \frac{w_i}{b_i} R \varphi \right) \right) \chi_i \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \chi_i - \chi_i \frac{w_i}{b_i} R \varphi \right]
\]

\[
\approx - \frac{w_i}{b_i} R \chi_i
\]

(41)

Then, take the Jacobian of \( \epsilon_{\chi \epsilon} \) with respect to the translational component of \( \frac{w_i}{b_i} \mathbf{P} \). Jacobians with respect to the translation portion of a pose are taken by perturbing the translation by \( R \delta t \), as in equation (15), and then taking the derivative with respect to the perturbation

\[
\mathbf{H}_{2} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \delta t} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \varphi}
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \frac{w_i}{b_i} R \left( G_i t_{\omega_0 b_i} - G_i t_{G_0 G_0 b_i} \right) \right) \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \mathbf{I}_i + \left( \frac{w_i}{b_i} R \varphi \right) \right) \chi_i \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \chi_i - \chi_i \frac{w_i}{b_i} R \varphi \right]
\]

\[
\approx - \frac{w_i}{b_i} R \chi_i
\]

(42)

The Jacobian of \( \epsilon_{\chi \epsilon} \), with respect to the rotational component of \( \frac{b_i}{G_i} \mathbf{P} \), again relies on the angle-axis perturbation method used in equation (41)

\[
\mathbf{H}_{2} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \delta t} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \varphi}
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \frac{w_i}{b_i} R \left( G_i t_{\omega_0 b_i} - G_i t_{G_0 G_0 b_i} \right) \right) \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \mathbf{I}_i + \left( \frac{w_i}{b_i} R \varphi \right) \right) \chi_i \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \chi_i - \chi_i \frac{w_i}{b_i} R \varphi \right]
\]

\[
\approx - \frac{w_i}{b_i} R \chi_i
\]

(43)

The Jacobian of \( \epsilon_{\chi \epsilon} \), with respect to the translational component of \( \frac{b_i}{G_i} \mathbf{P} \), relies on the same method as equation (42)

\[
\mathbf{H}_{2} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \delta t} = \frac{\partial \epsilon_{\chi \epsilon}}{\partial \varphi}
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \frac{w_i}{b_i} R \left( G_i t_{\omega_0 b_i} - G_i t_{G_0 G_0 b_i} \right) \right) \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \left( \mathbf{I}_i + \left( \frac{w_i}{b_i} R \varphi \right) \right) \chi_i \right]
\]

\[
= \frac{\partial}{\partial \varphi} \left[ \chi_i - \chi_i \frac{w_i}{b_i} R \varphi \right]
\]

\[
\approx - \frac{w_i}{b_i} R \chi_i
\]

(44)

By symmetry with equations (41) to (44), and accounting for sign differences when necessary, the Jacobians with respect to the rotational and translational components of \( \frac{b_i}{G_i} \mathbf{P} \) and \( \frac{b_i}{G_i} \mathbf{P} \) can be found

\[
\mathbf{H}_{3} = - \frac{w_i}{b_i} R \mathbf{R}_{b_i}
\]

\[
\mathbf{H}_{4} = \frac{w_i}{b_i} R \mathbf{R}_{b_i}
\]

(45)

\[
\mathbf{H}_{5} = \frac{w_i}{b_i} R \mathbf{R}_{b_i}
\]

(46)

Finally, the Jacobian with respect to the translation to the target’s center of mass \( \mathbf{G}_i t_{G_0 G_0 b_i} \) can be found

\[
\mathbf{H}_{5} = \frac{w_i}{b_i} R \mathbf{R}_{b_i}
\]

(47)

5.3. Center-of-mass prior factor

A prior Gaussian belief \( x^* = \mathbf{G}_i t_{G_0 G_0 b_i} \) is calculated based on information available at the first time step, recalling that
\[ \frac{\mathbf{G}}{\mathbf{b}_0} \mathbf{R} = \mathbf{I}_3 \]

\[ \mathbf{Z}_{\mathbf{a}_{\mathbf{b}_0}} = \mathbf{W} \mathbf{t}_{\mathbf{a}_{\mathbf{b}_0}} \mathbf{b}_0 - \frac{\mathbf{w}}{\mathbf{b}_0} \mathbf{R}^T \mathbf{w} \mathbf{t}_{\mathbf{a}_{\mathbf{b}_0}} \] (48)

Here, \( \frac{\mathbf{w}}{\mathbf{b}_0} \mathbf{R} \) and \( \mathbf{w} \mathbf{t}_{\mathbf{a}_{\mathbf{b}_0}} \) are obtained from the initial state prior belief \( \mathbf{z}^a \), and \( \mathbf{Z}_{\mathbf{a}_{\mathbf{b}_0}} \) is obtained from equation (27). A prior factor \( \phi_{i,k} \) with high covariance \( \Sigma_{i,k} \) is then placed on the position of the center of mass \( \mathbf{Z}_{\mathbf{a}_{\mathbf{b}_0}} \)

\[ P(\mathbf{z}^i | \theta_k) = \mathcal{N}(\mathbf{h}(\theta_k), \Sigma_{i,k}) \]

\[ \mathbf{z}^i \in \mathbb{R}^3, \quad \phi_{i,k} = ||\mathbf{z}^i - \mathbf{Z}_{\mathbf{a}_{\mathbf{b}_0}}||^2 \] (49)

5.4. Combined factor graph

When the rotation kinematic factor from Section 5.2 is attached to all five relevant variables, it connects the trajectory factor graph from Figure 3(a) with the mapping pose graph from Figure 3(b). Solving for the entire factor graph shown in Figure 3 is the preferred method for jointly estimating the trajectory, mapping the target, and determining the target’s center of mass.

5.5. Study of applicability

This section studies the applicability of the center-of-mass estimation technique considered herein for different inspector positions, rotation angles, and sampling frequencies. In this study, a spherical target with radius \( r_1 \) and normalized inertia ratios \( \mathbf{J} = \text{diag}(1.2, 1, 1) \) nutates about its major axis \( x_B \) for five nutation periods at a nutation angle of \( \beta \) (see Figure 7). An inspector is placed in the \( x_W - y_W \) plane at a latitude \( \lambda \) and distance \( r_i \); the \( x_W \) axis is aligned with the target’s angular momentum vector \( \mathbf{h}_B \). Under this rotational motion, the angular velocity \( \omega_B \) is constant; the frame rate of the inspector’s camera is set to take an image every \( t = \omega/\Delta\theta \) seconds. Pose noise with covariance \( \Sigma_P = \text{diag}(\sigma_R^2, \sigma_R^2, \sigma_I^2, \sigma_I^2, \sigma_I^2) \) where \( \sigma_R = 0.5^\circ \) and \( \sigma_I = 0.03 \) is applied to each inspector pose in the geometric frame \( \mathbf{b}_P \); no noise is added to inspector poses in the world frame \( \mathbf{b}_W \). Solutions for the center of mass are obtained using the linear method presented in Section 5.1. For each data point, 10 trials are performed; error bars are used to represent the standard deviation of the results.

5.5.1. Inspector position. The sensitivity of center-of-mass estimation accuracy to the position of the inspector is shown in Figure 8. For this experiment, \( \beta = 25^\circ \) and \( \Delta\theta = 20^\circ \). The polar orbit experiments correspond to single 360° circumnavigations of the target in the \( x_W - y_W \) plane. All other inspections are stationary at the specified latitude and distance. Inspections performed at close proximity yield more accurate results than distant inspections. For stationary inspections, lower latitudes have less error. However, a full polar orbit inspection yields results as accurate as those obtained from a stationary equatorial vantage point. In general, it is recommended that inspections be performed: at the closest safe distance at which the target remains entirely in the field of view; at a variety of vantage points; and in a symmetric manner (i.e., analyze data from a full relative orbit rather than a fraction thereof).

5.5.2. Nutation angle. The sensitivity of center-of-mass estimation to the nutation angle \( \beta \) is shown in Figure 9. For this experiment, \( r_i = 4 \) \( r_1 \), \( \Delta\theta = 20^\circ \), and a full polar orbit is performed. For small \( \beta \), the rotation is nearly entirely about a single-axis, making center-of-mass determination inaccurate. For larger values of \( \beta \), there is sufficient wobble in the
6. Implementation

This section outlines the acquisition of real and simulated test data, the determination of ground truth, and implementation of the algorithms described in Sections 3 to 5.

6.1. Data acquisition

6.1.1. International Space Station. Data from the ISS were obtained using the Synchronized Position Hold Engage and Reorient Experimental Satellites (SPHERES) laboratory for distributed satellite systems, which consists of a set of hardware and software tools developed for the maturation of metrology, control, and autonomy algorithms (Hilstad et al., 2010; Saenz-Otero, 2005).

SPHERES are micro-satellites that operate in a flat floor environment at MIT, on parabolic flights in temporary microgravity, and aboard the ISS in long-duration microgravity. They are able to maneuver in 6-DOF in microgravity (three degrees of freedom during ground operation), to communicate with each other and with a laptop control station, and to identify their position with respect to each other and to the experimental reference frame. State estimation on the SPHERES satellites is performed using an extended Kalman filter with inputs from gyroscopes, external ultrasonic beacons, and commanded forces and torques. The position and orientation accuracy of this system, which is called “global metrology” is nominally 1 cm and 3° respectively, but can degrade near the edges of the test volume (the space encompassed by the ultrasonic beacons). The SPHERES satellites run C code using an onboard digital signal processor; there are currently three SPHERES satellites on the ISS.

Stereoscopic image data were obtained using the Visual Estimation for Relative Tracking and Inspection of Generic Objects (VERTIGO) Goggles, a hardware addition to the SPHERES satellites that enables vision-based navigation research in the 6-DOF, microgravity environment on the ISS. Attaching to the SPHERES expansion port, the Goggles include a stereo camera, an embedded x86 Linux computer, and a high-speed wireless communication system (Tweddle, 2013; Tweddle et al., 2015). The VERTIGO Goggles computer runs C++ code including OpenCV and communicates with the SPHERES satellites via a serial port. Two VERTIGO Goggles units are currently on the ISS. The major components of the SPHERES-VERTIGO test platform are shown in Figure 11.

The experimental data presented herein were collected during SPHERES Test Session #53 Test #7, Run #3 on 24 January 2014. One SPHERES satellite with attached VERTIGO Goggles was given the role of inspector, and another was given the role of target. The target satellite was equipped with stickers (see Figure 11), adding texture to the satellite to aid in natural feature detection (Tweddle, 2013).

Control of the inspector’s orientation is performed by commanding the inspector to point toward the target’s visual motion of the target for the center of mass to be accurately determined.

5.5.3. Sampling frequency. The sensitivity of center-of-mass estimation accuracy to the sampling frequency is shown in Figure 10. For this experiment, $r_i = 4 r_t$, $\beta = 25^\circ$, and a full polar orbit is performed. Error is reduced by choosing a sampling frequency for which the target rotates significantly between image acquisitions. However, the choice of sampling frequency will also require practical consideration. To facilitate frame-to-frame feature matching, images must contain overlapping sections of the scene; additionally, there are limitations to the acceptable off-optical-axis scene rotation that can be accommodated by feature matching algorithms. Real-time processing considerations may limit the minimum $\Delta \theta$ for very quickly rotating target objects. A $\Delta \theta$ between 5° and 30° has been tested herein, with favorable results.

![Fig. 9. Sensitivity of center-of-mass estimation accuracy to nutation angle.](image)

![Fig. 10. Sensitivity of center-of-mass estimation accuracy to sampling frequency.](image)
The major components of the SPHERES-VER TIGO test platform (Tweddel, 2013). (Right) SPHERES-VER TIGO in operation aboard the ISS.

**Table 1.** Frequencies of logged data during ISS and simulated experiments.

<table>
<thead>
<tr>
<th></th>
<th>Test Session # 53</th>
<th>Simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stereo images (Hz)</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>Inertial measurement unit data (Hz)</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>Thruster firing times (Hz)</td>
<td>1000</td>
<td>1000</td>
</tr>
<tr>
<td>Global metrology (Hz)</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

centrold. To determine the visual centroid, a depth map is found using the Library for Efficient Large-Scale Stereo Matching (LIBELAS) (Geiger et al., 2010), and restricted to exclude the immediate foreground and the ISS background (a range of depths from 0.1–0.8 m was included). This thresholded depth map is then averaged to obtain a measurement of range and bearing to the target’s visual centroid. The command to point toward the target’s centroid does not constrain the inspector’s orientation about its camera’s optical axis, so the angular rate in this direction, as measured by the onboard gyroscopes, is commanded to zero. Datasets were logged during all tests using the measurement frequencies shown in Table 1. Figure 12 shows an example stereo image collected on the ISS.

6.1.2. Simulation. Dynamics simulation is performed using the SPHERES simulation, which uses a combination of MATLAB, Simulink, and C code compiled as binary MATLAB executable (MEX) files (SSL, 2016). Visual simulation is performed using the Blender 3D modeling and animation software (Blender, 2017). Inspired by a scene from the film *Interstellar*, in which the crew must dock to a spinning spacecraft, the visual model chosen for the target in this simulation is the *Endurance* spacecraft from the film. A visual model of *Endurance* was obtained from a Kerbal Space Program modification (Jewer, 2015). The true states resulting from the SPHERES simulation are scaled by $100 \times$ to generate the inspector’s camera positions in the Blender model. Blender’s Python interface is used to command the poses of the target and the inspector’s left and right cameras; a full grayscale 3D rendering with a space background is performed at each time step to create a sequence of stereo images similar to that obtained using SPHERES-VER TIGO (see Figure 13). Despite the scaling to generate camera vantage points in Blender, VERTIGO’s camera calibration parameters are used in data analysis, so all results herein are at the scale of the SPHERES test platform.

6.2. Experimental design

Two separate tests are performed herein to validate the trajectory estimation, mapping, and center-of-mass determination algorithm on ISS and simulated data.

6.2.1. ISS test. A target SPHERES satellite is commanded to hold position at the origin of the SPHERES test volume; its orientation is made to emulate a passive intermediate axis spin with small off-axis components, using the CAD-determined SPHERES inertia ratios. Once the thrusters properly establish the spin, orientation control is removed from the target satellite and it is allowed to rotate passively. The inspector SPHERES satellite is commanded to stay at a fixed distance from the target’s visual centroid, allowing the inspector to move freely in a sphere surrounding the target. During this test, disturbance forces inside the ISS, probably resulting from airflow, led to an inspector trajectory that circumnavigated the target in a nearly perfect circle.

6.2.2. Simulated test. A (simulated) target SPHERES satellite is commanded to hold position and orientation near the center of the SPHERES test volume. The (simulated)
inspector SPHERES satellite is made to circumnavigate the target satellite in a free-orbit ellipse. The position of the inspector’s center of mass is commanded to follow a simulated 1.1 m × 0.55 m, 5 min free-orbit ellipse (scaled down from 110 m × 55 m and 91.4 min to fit within the dimensions and time constraints typical of SPHERES tests). The orientation of the target is commanded to emulate a low-energy, torque-free, major-axis spin with small off-axis components, using the inertia ratios of a short ring with a large radius.

6.3. Ground truth determination

6.3.1. International Space Station. Ground truth orientation estimates are obtained by solving a separate visual-inertial odometry factor graph (see Figure 14) using features in the static ISS background (1–5 m from the camera). The same visual odometry procedure described in Section 4.2 is used to provide pose constraints between two subsequent inspector states in a visual-inertial odometry coordinate frame \( V \). The visual odometry estimates are then aligned with the global metrology estimates by finding the optimal rotation \( W^r R \). The ground truth inspector pose comprises a visual-inertial orientation estimate and a global metrology translation estimate. The ground truth for the target pose is provided exclusively by global metrology, since the target does not have an attached stereo camera.

The ground truth for the location of the target’s center of mass \( \Xi_{\text{GeoB}} \) is not determined since its calculation requires the use of global metrology estimates whose errors are expected to be of the same order as, or larger, than errors in center-of-mass determination. Comparison of the generated 3D map with the SPHERES CAD model is used in lieu of comparison with a ground truth value.

6.3.2. Simulation. The ground truth output from the dynamics simulation is recorded at 5 Hz. The ground truth states of both the inspector and the target are thus available for every time step.

The ground truth for the translation to the center of mass \( \Xi_{\text{GeoB}} \), is calculated by averaging the position of the \( M_{\text{in}} \) inliers in the first frame and using the ground truth states to determine its exact location, as

\[
\Xi_{\text{GeoB}} = \Xi_{\text{GeoB}0} + \Xi_{\text{GeoB}0} r + \Xi_{\text{W0}B0} \nonumber
\]

\[
= \frac{1}{M_{\text{in}}} \sum_{i=1}^{M_{\text{in}}} \Xi_{\text{GeoB0}} t_{\text{B0}0} p_i \ldots + \frac{\Xi_{\text{GeoB0}}}{M_{\text{in}}} R \left( -\Xi_{\text{W0}B0} + \Xi_{\text{W0}B0} \right)
\]

Here the position of an inlier in the first body frame \( B_0 \) is given by \( \Xi_{\text{B0}0} t_{\text{B0}0} p_i \).
6.4. Implementation

The trajectory estimation and mapping algorithms described in Sections 3 to 5 are implemented in C++ using the publicly available GTSAM 4.0 library (Dellaert and Beall, 2017). Each variable and factor from the combined factor graph presented in Section 5.4 is built up using GTSAM classes, as listed in Table 2. The built-in BearingRangeFactor is modified to accept a transform between the body and the sensor pose, resulting in the upgraded factor BearingRangeFactorWithTransform. The inertial odometry factor is implemented using the CombinedImuFactor, with gravity set to zero. The RotationKinematicFactor is novel and created from scratch (see Setterfield (2017b) for source code).

The prior factor $\phi_0$ is initialized using the global metrology estimate closest to the test start time. For ISS data, star tracker measurements are obtained from the ground truth orientation estimates calculated in Section 6.3.1. For simulated data, star tracker measurements are obtained by adding zero-mean Gaussian noise $\Sigma_s = \text{diag}([\sigma_x^2, \sigma_y^2, \sigma_z^2])$, with $\sigma_s = 200$ arcseconds to the simulation ground truth orientation in the world frame.

The principal image processing steps as performed on one image are shown in Figure 15. Incoming images from the ISS dataset (but not the simulated dataset) are equalized to increase their contrast and the quantity of detected features. Range and bearing measurements are obtained by averaging a thresholded depth map produced by LIBELAS, as described in Section 6.1.1. The bias in range measurements caused by seeing only the front side of the target is corrected for as in Setterfield (2017a, p. 142).

The thresholded depth map is then used to create a bounding box around the object to restrict the search space for features (see the blue rectangle in Figure 15). Four octaves of non-upright SURF features with a Hessian threshold of 400 are detected using OpenCV 2.4.6.1 (OpenCV, 2013). 3D stereo frames are formed by triangulating all of the detected features that satisfy the epipolar constraints discussed in Section 4.2.

Frame-to-frame matching and visual odometry between each current stereo frame and the respective previous stereo frame are attempted at each iteration using custom C++ implementations of absolute orientation and maximum-likelihood estimation (Setterfield, 2017a). If a valid motion estimate is not obtained between the previous frame and the current frame, the algorithm continues to seek a match between the previous frame and subsequent frames until one is found (this is referred to as reacquisition herein). A motion estimate is considered valid if $M_{\text{in}} \geq 6$ inliers are found (or $M_{\text{in}} \geq 10$ for reacquisition), and the estimated motion is under $45^\circ$ and 0.5 m in rotation and translation, respectively. Nodes $x_i$ and $\theta$ of the factor graph presented in Section 5.4 are added only when a valid frame-to-frame motion estimate has been obtained.

Loop closure, as discussed in Section 4.2, is attempted between the current time step and between one to three previous time steps $h$. At time step $j$, the stereo frames from time steps 0 through $j - N_k$ ($N_k = 5$) are divided into three equal sets. Firstly, a time step $h_1$ from the oldest set is
selected at random, and loop closure is attempted; if unsuccessful, loop closure is attempted with a randomly selected time step $h_2$ from the second set; if this is again unsuccessful, loop closure is attempted with a randomly selected time step $h_3$ from the newest set. This methodology encourages loop closures with early poses. Loop closures are considered valid if all the conditions for a valid reacquisition are met, and the current estimated inspector pose in the geometric frame $P^{b}$ is within 20° of the pose at the time step of loop closure $P^{b}$. This rotation proximity requirement for loop closure is used to avoid erroneous loop closures.

These nodes and all connected factors are added to an ISAM2 factor graph optimizer (Kaess et al., 2012). Estimation is performed incrementally, meaning that an estimate of all variables is available at every time step. When not otherwise stated, the results presented herein are the iSAM2 results from the final time step.

7. Results

This section outlines the results of algorithm validation, and the computational performance and convergence of the algorithms. Herein, scalar errors in estimated position $t$ and orientation $R$ with respect to ground truth values $\bar{t}$ and $\bar{R}$ are given as

$$\delta t = \| t - \bar{t} \| \tag{51}$$

$$\delta \theta = [\delta \theta_1 \, \delta \theta_2 \, \delta \theta_3]^T = \text{Log} \left( \bar{R}^T R \right), \quad \delta \theta = \| \delta \theta \| \tag{52}$$

In the presented results, three-dimensional frames are depicted by triads, for which red, green, and blue lines represent the $x$, $y$, and $z$ axes, respectively.

7.1. ISS test

Data obtained from the test described in Section 6.2.1 were used to validate trajectory estimation and mapping experimentally. The image processing, mapping, and center of mass determination pipeline may be viewed in Video 1; the resulting map may be viewed in Video 2. A summary of the estimated pose of the inspector is shown at the left and top right ($\times 2$) of Figure 16. Errors in trajectory estimation are shown in the top ($\times 2$) plots of Figure 17. This estimation accuracy is acceptable for disambiguating the motion of the inspector from that of the target so that mapping and center-of-mass determination can be performed.

The rotation $G^{R}$ from the target’s body frame to its geometric frame is estimated as described in Setterfield (2017a). The true and estimated orientations of the target’s body frame are shown at the bottom right of Figure 16. The error in the estimated orientation is shown in the bottom plot of Figure 17, with an average value of 15.0°. Three major factors could contribute substantially to this discrepancy. Firstly, the ground truth frame in which the inspector’s trajectory is estimated differs by 5.4°, on average, from the global metrology frame. This means that measurements are being compared from two slightly different coordinate frames. Secondly, the target is spinning at approximately 60°/s, and global metrology is measured at 5 Hz, or every 0.2 s. Herein, the visual estimates are compared with the temporally closest global metrology estimates, which could have occurred up to 0.1 s earlier or later. This results in a global metrology measurement that may differ by up to 6° in orientation from its true value at the time it was visually observed. Finally, it is possible that there is a small error in estimation of $G^{R}$ in Setterfield (2017a).

A feature map of the SPHERES satellite obtained during this test is shown in Figure 18(a). As expected, the triad for the geometric frame $G$ lies at the center of the purple first inlier points. Inlying SURF features are depicted by
Fig. 16. Results from the ISS test. (Left) Pose history of the inspector. The green dot represents the start of the trajectory, the triads represent the $B$ frame, the blue and orange dots represent the end of the global metrology and the estimated trajectory, respectively, and the red dot represents the center of mass of the target. (Top right ×2) Pose history of the inspector $\{W^t_{W^B^t}B^q\}$. (Bottom) Target orientation $B^q_W$. colors pertaining to the order in which they are detected; from oldest to newest, they are colored blue, green, orange, and yellow. Outlying SURF features are depicted as small, gray points. The 3D map of the target SPHERES satellite is compared with a 3D CAD model in Figure 18(b). To perform this comparison, the feature map and 3D model are rotated and translated into the estimated and true body frames, respectively. The 3D feature map closely resembles the CAD model; this is especially true for the inliers, shown in green. The closeness of fit between the point cloud and the 3D map demonstrates that the center of mass has been successfully estimated. The superior quality of the inlying visual features suggests that a feature map for use in subsequent relative pose estimation should include only inlying points. Each of the 6684 inlying features has an associated feature descriptor, providing ample features for use in relative pose estimation.

Fig. 17. Estimation errors in the ISS test.

7.2. Simulated test

Data obtained from the test described in Section 6.2.2 were used to validate trajectory estimation and mapping in the simulation. The image processing, mapping, and center of mass determination pipeline may be viewed in Video 3; the resulting map may be viewed in Video 4. A summary of the estimated pose of the inspector is shown at the left and top right (×2) of Figure 19. Errors in trajectory estimation are shown in the top (×2) plots of Figure 20. The rotation $G^B_R$ from the target’s body frame to its geometric frame is estimated as described in Setterfield (2017a). The true and estimated orientations of the target’s body frame are shown at the bottom right of Figure 19. The error in the estimated orientation is shown in the bottom plot of Figure 20, with an average error of 1.4°. The errors in the final estimate of the target’s center of mass are shown in Table 3.
Fig. 18. (a) Estimated map and body axes of the target SPHERES satellite. (b) Comparison of feature map with a 3D CAD model of the SPHERES satellite.

Fig. 19. Results from the simulated test. (Left) Pose history of the inspector. The green dot represents the start of the trajectory, the triads represent the $B$ frame, the blue and orange dots represent the end of the global metrology and estimated trajectory, respectively, and the red dot represents the center of mass of the target. (Top right $\times 2$) Pose history of the inspector $\{W_tW_{t0B}, B_{W_t}q\}$. (Bottom) Target orientation $B_{W_t}q$.

Table 3. Errors in the final estimates of center of mass in the simulated test.

<table>
<thead>
<tr>
<th>Direction in $G$</th>
<th>True $\hat{B}_{GtoB}$</th>
<th>Estimated $\hat{B}_{GtoB}$</th>
<th>Error magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x$ (m)</td>
<td>0.0565</td>
<td>0.0581</td>
<td>0.0016</td>
</tr>
<tr>
<td>$y$ (m)</td>
<td>0.0078</td>
<td>0.0049</td>
<td>0.0029</td>
</tr>
<tr>
<td>$z$ (m)</td>
<td>−0.0213</td>
<td>−0.0256</td>
<td>0.0043</td>
</tr>
<tr>
<td>Total (m)</td>
<td></td>
<td></td>
<td>0.0054</td>
</tr>
</tbody>
</table>

A map of the Endurance spacecraft is shown in Figure 21(a). The geometric frame $G$ is shown, together with the estimated translation to the center of mass of the spacecraft, which is located in the middle of the central module. The feature map is compared with the original Blender model of the spacecraft in Figure 21(b). Most inliers, shown in green, surround the surface of the spacecraft, as desired. Some features resulting from faulty correspondences of stars passed both the depth thresholding and the visual odometry inlier checks and do not lie on the surface of the model; this is especially true near the center of mass, where minimal feature motion is present. These features are unlikely to affect future relative pose estimates, since the correspondence of these separate stars is a result of a specific vantage point; if seen again, they will probably be outnumbered by inlying features.
Retired geostationary satellites have been found to spin at rates between 0.06°/s and 2.6°/s (Binz et al., 2014), indicating rotational speeds that are between 9.8 and 1000 times slower than those considered herein (60°/s for the ISS test and 25.5°/s for the simulated test). In the simulated test, a 91.4 min free-orbit ellipse in low-Earth orbit is compressed by a factor of 18.3× into a 5 min time period. Therefore, it is reasonable to view the tests conducted in this paper as an analog for low-Earth orbit proximity operations sped up by a factor of 18.3 and scaled down in physical dimensions by a factor of 100. This analogy is used when assessing the real-time applicability of the algorithms herein.

7.3. Computational performance and convergence

Trajectory estimation and mapping using GTSAM is solved using a Linux virtual machine running Ubuntu Linux 10.04. The virtual machine is hosted on an Intel Core i7-3630QM 2.4 GHz laptop and allocated two cores and 8 GB of RAM.

![Inspector Position Error](image)

**Fig. 20.** Estimation errors in the simulated test.

![Inspector Orientation Error](image)

![Target Orientation Error](image)

7.3.1. ISS test. The total computation times of the algorithms in the ISS test are shown in Table 4. When scaled temporally by 18.3×, as discussed, the 153 s ISS test inspecting a target spinning at approximately 60°/s becomes a 46.7 min test of a target spinning at 3.3°/s and the 22.9 min of computation can then be performed in real time within the inspection period (if the onboard computer has similar computational capabilities to the one used herein). The iSAM2 algorithm developed in this paper accounts for just 0.12% of the total computation time. Therefore, any inspector satellite capable of performing the requisite image processing for inspection of an on-orbit object in real time will also be able to run the algorithms presented in this paper in real time at minimal extra computational cost.

The computation times for each image are shown in Figure 22. Equalization is computationally inexpensive, taking approximately 1.5 ms per image. A visual lock on the target is lost from images 12 to 22 and 222 to 232. During these periods, no nodes were created and loop closure was not attempted. The bottom plot in Figure 22 shows the iSAM2 computation times in more detail. Spikes in computation time correspond to successful loop closures. Disregarding loop closures, iSAM2 computation time increases.

![Fig. 21.](image)
Table 4. Total algorithm computation times in ISS test.

<table>
<thead>
<tr>
<th>Number of images</th>
<th>310</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>287</td>
</tr>
<tr>
<td>Number of loop closures</td>
<td>10</td>
</tr>
<tr>
<td>Equalize</td>
<td>0.460 s 0.034%</td>
</tr>
<tr>
<td>Range and bearing measurement</td>
<td>169.9 s 12.4%</td>
</tr>
<tr>
<td>Stereo frame acquisition</td>
<td>625.4 s 45.6%</td>
</tr>
<tr>
<td>Visual odometry</td>
<td>143.8 s 10.5%</td>
</tr>
<tr>
<td>Loop closure</td>
<td>431.5 s 31.4%</td>
</tr>
<tr>
<td>iSAM2</td>
<td>1.66 s 0.12%</td>
</tr>
<tr>
<td>Total</td>
<td>1372.7 s 100%</td>
</tr>
</tbody>
</table>

Table 5. Total algorithm computation times in simulated test.

<table>
<thead>
<tr>
<th>Number of images</th>
<th>311</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>310</td>
</tr>
<tr>
<td>Number of loop closures</td>
<td>10</td>
</tr>
<tr>
<td>Equalize</td>
<td>0 s 0%</td>
</tr>
<tr>
<td>Range and bearing measurement</td>
<td>226.1 s 19.7%</td>
</tr>
<tr>
<td>Stereo frame acquisition</td>
<td>400.8 s 34.9%</td>
</tr>
<tr>
<td>Visual odometry</td>
<td>131.1 s 11.4%</td>
</tr>
<tr>
<td>Loop closure</td>
<td>386.1 s 33.6%</td>
</tr>
<tr>
<td>iSAM2</td>
<td>3.30 s 0.29%</td>
</tr>
<tr>
<td>Total</td>
<td>1147.4 s 100%</td>
</tr>
</tbody>
</table>

linearly at approximately 15.0 µs per image over the duration of the test. An increased computational load associated with loop closure and a complexity between $O(1)$ and $O(N^3)$ are predicted for iSAM2 by Kaess et al. (2012). The complexity of iSAM2 optimization for the combined factor graph in this paper appears to be approximately $O(N)$ for problems of the size tested.

7.3.2. Simulated test. The total computation times of the algorithms in the simulated test are shown in Table 5. When scaled temporally by $18.3 \times$, as discussed, the 19.1 min of computation time can be performed nearly in real time within the 18.7 min inspection period. The iSAM2 estimation algorithm developed in this paper accounts for just 0.29% of the total computation time.

The computation times for each image are shown in Figure 23. Stereo frame acquisition is, in general, much faster than in the ISS case. This is because extended SURF-128 feature descriptors are used in the ISS case, whereas the standard SURF descriptors are used in the simulated case; while providing improved feature matching, the extended descriptor is more computationally expensive to extract and match (Bay et al., 2006). The iSAM2 computation times in the bottom plot of Figure 23 exhibit the same behavior as in the ISS test; during this test, the rate of iSAM2 computation time increase is approximately 20.2 µs per image.

8. Conclusions and future work

This paper addresses on-orbit inspection of a rotating object using a moving observer, seeking a sufficiently detailed and accurate estimate of the target's appearance and center of mass to aid in the planning and execution of subsequent proximity operations.

To disambiguate the motion of the inspector from that of the target, a novel trajectory estimation algorithm was used...
(Setterfield et al., 2017). Efficient mapping algorithms were created, together with a novel “rotation kinematic factor”. This factor links the dynamics of the inspector with that of the target and is used to determine the target’s center of mass.

These algorithms were validated experimentally on the ISS, as well as in simulation. The computational cost of the developed algorithms was shown to be minimal compared with that of the image processing required for on-orbit inspection.

Lighting conditions and specularity of the target will make application of the algorithms in this paper difficult when using a passive visual sensor, such as a stereo camera (as opposed to an active visual sensor, such as LiDAR). It is possible to investigate strategies for coping with these issues using 3D rendering software. In this software, surface properties of the satellite can be set, as well as sun direction and intensity; these parameters could be adjusted to emulate on-orbit lighting conditions with high fidelity.

As shown in Section 4, it is always possible to create a feature map of the target, regardless of whether the target is subject to external torques. This is because mapping is done in a target-fixed frame. The self-contained pose graph shown in Figure 3(b) highlights the separability of mapping the target from the dynamics of the inspector. Solution of this visual odometry pose graph in isolation would facilitate mapping for arbitrary target motion, even if the target is acted on by unknown external forces.

When an unknown target object does not undergo rotation with respect to the inertial frame, the best estimate of its center of mass is obtained by assuming that it has uniform density, and averaging the volume contained by the 3D map of the object. When the target undergoes single-axis rotation, its axis of rotation is observable, but the exact location of the center of mass is not; the best estimate of the center of mass is then the projection of the 3D map’s volumetric center onto this axis. When the target undergoes multi-axis rotation, its center of mass is observable. Center-of-mass determination is applicable for passive and active targets, provided that they are not acted on by unknown external forces.

This paper sought to advance previous techniques for on-orbit inspection of uncooperative objects. Algorithms for trajectory estimation, mapping, and center-of-mass estimation have been developed. Their validation, both experimentally and in simulation, has demonstrated that a substantial portion of the information required for proximity operations can be accurately and efficiently observed during a preliminary inspection phase. The tools presented herein are a stepping-stone for future work that may lead to missions involving autonomous satellite repair, the capture and removal of space debris, and the exploration of near-Earth asteroids.

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Appendix: Index to multimedia extensions

Archives of IJRR multimedia extensions published prior to 2014 can be found at http://www.ijrr.org, after 2014 all videos are available on the IJRR YouTube channel at http://www.youtube.com/user/ijrrmultimedia

Table of multimedia extensions

<table>
<thead>
<tr>
<th>Extension</th>
<th>Media type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Video</td>
<td>Mapping and determining the center of mass of a SPHERES satellite on the ISS (2.5x speed)</td>
</tr>
<tr>
<td>2</td>
<td>Video</td>
<td>Rotating view of the completed map of a SPHERES satellite</td>
</tr>
<tr>
<td>3</td>
<td>Video</td>
<td>Mapping and determining the center of mass of the simulated Endurance spacecraft (2.5x speed).</td>
</tr>
<tr>
<td>4</td>
<td>Video</td>
<td>Rotating view of the completed map of the Endurance spacecraft.</td>
</tr>
</tbody>
</table>