

ADAPTIVE GNSS-BASED RELATIVE NAVIGATION FOR CLOSE FORMATION FLYING UNDER CONTINUOUS LOW-THRUST

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Distributed Earth Observation missions are increasingly relying on formation-flying architectures to enhance payload performance beyond the limitations of single-spacecraft systems. In particular, concepts employing inter-satellite baselines of only a few metres have attracted significant interest, although they require continuous thrusting and place stringent demands on the relative GNC system. This work investigates the feasibility of GNSS-based relative navigation for achieving the navigation performance required by such missions. An EKF-based navigation architecture is developed, exploiting single-frequency GPS and Galileo measurements through the combination of GRAPHIC and single-differenced carrier-phase observables. To improve robustness against modelling uncertainties associated with continuous low-thrust actuation, an Adaptive Dynamic Model Compensation approach is integrated within the filter and compared against a baseline EKF employing fixed process noise. The proposed algorithms are assessed in a representative formation-maintenance scenario derived from the TriHex mission concept, involving three metre-class spacecraft flying with inter-satellite distances of approximately 5 m. Simulation results demonstrate that GNSS-only relative navigation can achieve millimetre-level relative positioning accuracy under continuous control. The adaptive approach significantly improves robustness during filter initialisation, enabling reliable convergence even when the initial process-noise levels are insufficient for a conventional EKF. Once steady-state conditions are reached, however, only limited improvements in navigation accuracy are observed. Overall, the obtained results provide further evidence of the feasibility of GNSS-based autonomous relative navigation for future metre-level distributed Earth Observation missions.

INTRODUCTION

Modern Earth Observation (EO) systems are increasingly moving towards distributed space architectures, where multiple spacecraft cooperate to accomplish remote sensing tasks that would be difficult or impossible for a single satellite. By distributing instruments across several platforms, formation-flying missions can overcome limitations imposed by spacecraft size and launch constraints, enabling enhanced measurement capabilities and improved mission performance.

One application benefiting from this paradigm is passive microwave radiometry at L-band frequencies. In such missions, several spacecraft can operate as a synthetic aperture instrument, combining observations collected by individual receivers to emulate a significantly larger antenna aperture.¹ Achieving the desired measurement performance often requires relative separations of only

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a few metres, maintained through continuous control action.² These missions typically involve metre-class spacecraft, whose physical dimensions may become comparable to the formation baseline itself. Consequently, precise relative navigation and robust collision avoidance become critical mission-enabling capabilities.

The stringent navigation requirements associated with close-proximity operations naturally motivate the use of autonomous onboard estimation techniques. Among the available technologies, GNSS has become the preferred solution for navigation in Low Earth Orbit (LEO), both for absolute and relative real-time navigation and post-facto orbit determination. GNSS-based relative navigation has already been successfully demonstrated in several formation-flying missions, including PRISMA,³ TanDEM-X,⁴ and CanX-4/5,⁵ all of which relied on Extended Kalman Filter (EKF) architectures processing single-frequency GNSS measurements. Research activities have further advanced the achievable navigation performance. The DiGiTaL navigation system,⁶ for example, demonstrated sub-centimetre relative positioning accuracy through the exploitation of multi-GNSS carrier-phase observations. Despite these achievements, existing studies have largely focused on formations characterised by relatively large inter-satellite separations and impulsive control strategies. Very-close formations maintained through continuous low-thrust actuation remain considerably less explored.

Continuous thrusting introduces a further challenge for navigation because discrepancies between the commanded and actual control accelerations generate modelling errors that are difficult to characterise a priori. Under these conditions, adaptive filtering techniques offer a potential means of improving estimation robustness by adjusting the stochastic description of the filter to reflect the current dynamical environment. Several adaptive navigation approaches have been proposed in the literature. Early work by Busse et al.⁷ introduced covariance-matching techniques for formation-flying navigation, while Fraser and Ulrich⁸ investigated adaptive EKF formulations based on maximum-likelihood estimation and fuzzy-logic covariance tuning. Although effective, many adaptive approaches require heuristic mechanisms to guarantee physically admissible covariance estimates. A more rigorous framework was later introduced by Stacey and D’Amico⁹ through the Adaptive Dynamic Model Compensation (ADMC) approach, where covariance matching is combined with dynamical constraints through a constrained weighted least-squares formulation, ensuring consistency between the estimated process noise and the underlying system dynamics.

Against this background, the present work evaluates the applicability of GNSS-only autonomous relative navigation to metre-scale formation-flying missions operating under continuous low-thrust control. An adaptive EKF based on the ADMC framework is developed and compared with a conventional EKF implementation. The assessment is carried out using a representative formation-maintenance scenario involving three spacecraft separated by only a few metres. The obtained results contribute to the feasibility assessment of future distributed Earth-observation missions by quantifying the navigation performance achievable with GNSS measurements alone and by evaluating the benefits of adaptive process-noise estimation in close-proximity operations.

RELATIVE NAVIGATION FILTER

This section presents the design of the onboard relative navigation EKF adopted for close-proximity formation flying. The study focuses on a three-spacecraft formation in LEO. Since the considered mission concepts involve metre-class satellites, onboard computational resources are assumed to be sufficient to support the proposed estimation architecture.

Given the small inter-satellite separations, navigation reliability is a key requirement. To increase robustness against spacecraft failures, each satellite runs an independent navigation filter while estimating the states of all spacecraft in the formation. This distributed architecture enables continued mission operations even in the event of a temporary or permanent loss of navigation capability on one spacecraft.

GNSS Measurement Model

The proposed navigation architecture relies on the exchange of raw GNSS measurements among the spacecraft, allowing each satellite to independently estimate the full relative state of the formation. Commanded thrust profiles generated by the control system are also shared and used as inputs to the filter.

The measurement model follows the approach successfully adopted in previous flight demonstrations and relative navigation systems studies.^{3,6} In particular, the filter employs the GRAPHIC (GRoup And PHase Ionospheric Calibration) and Single-Difference Carrier-Phase (SDCP) combinations. The former mitigates ionospheric errors by exploiting the opposite sign of the ionospheric delay in pseudorange and carrier-phase measurements, while the latter provides high-accuracy relative positioning information.

These combinations are formed from single-frequency measurements, which in this work are obtained from both the GPS and Galileo constellations, specifically the L1C and E1 signals. GPS is selected due to its extensive heritage in space-based navigation, while Galileo is included for its improved signal quality and performance characteristics.¹⁰

State Definition and Process Model

Each spacecraft runs its own EKF while estimating the state of all members of the formation. The filter estimates the inertial position $\mathbf{r}$ and velocity $\mathbf{v}$ of each spacecraft, together with a set of empirical accelerations $\mathbf{a}_{emp}$ expressed in the Radial-Transversal-Normal (RTN) frame to capture unmodelled dynamical effects. In addition, the receiver clock bias and drift ($c\delta t$, $c\dot{\delta t}$) of the host spacecraft i are estimated, along with the relative clock bias and drift of the remaining spacecraft. For spacecraft j , these quantities are defined as:

$$\Delta(c\delta t)_{j/i} = c(\delta t_j - \delta t_i), \quad \Delta(c\dot{\delta t})_{j/i} = c(\dot{\delta t}_j - \dot{\delta t}_i) \quad (1)$$

An analogous formulation applies to satellite k . Finally, the use of carrier-phase measurements requires the estimation of carrier-phase ambiguities. These are estimated as absolute for the host spacecraft (N_i) and as single-differenced quantities for the other spacecraft (N_{SD}). The full state vector is then defined as:

$$\mathbf{x} = [\mathbf{x}_i \quad \mathbf{x}_{j/i} \quad \mathbf{x}_{k/i}]^T \quad (2)$$

with

$$\begin{aligned} \mathbf{x}_i &= [\mathbf{r}_i \quad \mathbf{v}_i \quad \mathbf{a}_{emp,i} \quad c\delta t_i \quad c\dot{\delta t}_i \quad N_i] \\ \mathbf{x}_{j/i} &= [\mathbf{r}_j \quad \mathbf{v}_j \quad \mathbf{a}_{emp,j} \quad \Delta(c\delta t)_{j/i} \quad \Delta(c\dot{\delta t})_{j/i} \quad N_{SD,ij}] \\ \mathbf{x}_{k/i} &= [\mathbf{r}_k \quad \mathbf{v}_k \quad \mathbf{a}_{emp,k} \quad \Delta(c\delta t)_{k/i} \quad \Delta(c\dot{\delta t})_{k/i} \quad N_{SD,ik}] \end{aligned} \quad (3)$$

It should be noted that a complete multi-GNSS formulation would require the estimation of inter-system biases (ISBs) to account for constellation-dependent timing and hardware effects. In this

preliminary study, the ISB is not explicitly estimated. Instead, the GPS-to-Galileo Time Offset (GGTO) broadcast in the Galileo navigation message is used to compensate for the inter-system time difference.

The prediction step is performed through numerical integration of the state and variational equations in the inertial frame. To reduce computational burden, the force model includes only the Earth's geopotential, represented by the GGM01S gravity model¹¹ up to degree and order 20. All remaining unmodelled forces are absorbed by the empirical acceleration states. These accelerations are modelled as a first-order Gauss-Markov process:

$$\mathbf{a}_{emp}(t + \Delta t) = e^{-\frac{\Delta t}{\tau}} \mathbf{a}_{emp}(t) + \omega(t) \quad (4)$$

where ω is a white Gaussian driving noise with covariance matrix $\mathbf{Q}_{a_{emp}}$. Each diagonal entry of $\mathbf{Q}_{a_{emp}}$ is given by

$$Q_{a_{emp},\gamma} = q_\gamma \frac{\tau_\gamma}{2} \left(1 - e^{-\frac{2\Delta t}{\tau_\gamma}} \right) = \sigma_\gamma^2 \left(1 - e^{-\frac{2\Delta t}{\tau_\gamma}} \right) \quad (5)$$

where q_γ is the noise power spectral density for each component γ in the RTN frame, τ_γ is the autocorrelation time constant, σ_γ is the standard deviation of that component of the empirical acceleration, and Δt is the filter time step. Following the Dynamic Model Compensation (DMC) approach, the process noise $\mathbf{Q}_{dyn}$ associated with the dynamical states ($\mathbf{r}, \mathbf{v}, \mathbf{a}_{emp}$) is computed as described in Reference 12.

The receiver clock bias and drift are modelled as a two-state random-walk process driven by white noise:

$$\begin{bmatrix} c\delta t(t + \Delta t) \\ c\dot{\delta}t(t + \Delta t) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} c\delta t(t) \\ c\dot{\delta}t(t) \end{bmatrix} + \mathbf{w}_{clk}(t) \quad (6)$$

where $\mathbf{w}_{clk} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_{clk})$ and the process noise covariance matrix $\mathbf{Q}_{clk}$ is derived as:

$$\mathbf{Q}_{clk} = \begin{bmatrix} S_f \Delta t + S_g \frac{\Delta t^3}{3} & S_g \frac{\Delta t^2}{2} \\ S_g \frac{\Delta t^2}{2} & S_g \Delta t \end{bmatrix} \quad (7)$$

where the terms S_f and S_g are related to the standard Allan variance parameters (h_0, h_{-2}) by $S_f = h_0/2$ and $S_g = 2\pi^2 h_{-2}$.¹³ For relative clock states, assuming identical uncorrelated oscillators, the covariance becomes $\mathbf{Q}_{clk,rel} = 2\mathbf{Q}_{clk}$.

Finally, carrier-phase ambiguities are propagated as constants during the time update and estimated as float parameters. Following filter convergence, the single-differenced ambiguities N_{SD} are fixed to integer values using the LAMBDA method,¹⁴ following the procedure described by Giraldo and D'Amico.⁶

ADAPTIVE FILTERING

To enhance the robustness of the filter, the integration of adaptive techniques has been investigated. In this work, the ADMC approach is adopted, as it integrates naturally with the Dynamic Model Compensation (DMC) framework already employed in the baseline EKF, thereby preserving the dynamical consistency of the model. This adaptive technique operates exclusively on the stochastic model associated with the dynamical states, namely position, velocity, and empirical accelerations. The process noise of all remaining states, including the clock and ambiguity parameters, is kept constant throughout the estimation process. Unless otherwise specified, the process noise

covariance matrix $\mathbf{Q}$ henceforth refers to the process noise associated with the dynamical states only.

The core of ADMC is a constrained weighted least squares minimisation that, at each time step, estimates the power spectral density values of the empirical acceleration process noise such that the resulting process noise covariance best matches the empirical covariance of the position and velocity state residuals. The solution is constrained within specified bounds to ensure physically meaningful values.

$$\tilde{\mathbf{q}} = \arg \min_{\mathbf{q}} \left(\mathbf{X}_k \mathbf{q} - \hat{\mathbf{Q}}_{ss}^{\text{vec}} \right)^T \mathbf{W}_k^{-1} \left(\mathbf{X}_k \mathbf{q} - \hat{\mathbf{Q}}_{ss}^{\text{vec}} \right) \quad \text{s.t. } \mathbf{q}_l \leq \mathbf{q} \leq \mathbf{q}_u \quad (8)$$

where $\mathbf{q}$ contains the power spectral densities of the empirical acceleration states, $\mathbf{X}_k$ maps $\mathbf{q}$ to the process noise covariance of the spacecraft state, $\hat{\mathbf{Q}}_{ss}^{\text{vec}}$ is the vectorised empirical covariance of the position and velocity states, $\mathbf{W}_k$ is a weighting matrix, and $\mathbf{q}_l$ and $\mathbf{q}_u$ define admissible lower and upper bounds. In this work, the matrix $\mathbf{X}_k$ differs from the formulation proposed by Stacey and D'Amico,⁹ as it also accounts for the rotation between the RTN frame, in which the empirical accelerations are defined, and the inertial (ECI) frame, in which the spacecraft state is expressed. The process noise covariance matrix at time step k is obtained by:

$$\tilde{\mathbf{Q}}_k = (1 - \alpha) \tilde{\mathbf{Q}}_{k-1} + \alpha \tilde{\mathbf{Q}}_k^* \quad (9)$$

where α is a smoothing factor and $\tilde{\mathbf{Q}}_k^*$ is obtained from the solution of Eq. (8). In this work, α is set to 0.1, as this value was found to provide satisfactory performance for the considered application. When applied to the formation flying scenario, the adaptation is carried out independently within each onboard EKF. This is due to the way the empirical covariance is computed:

$$\hat{\mathbf{Q}}_k = \frac{1}{N} \sum_{p=k-N}^{k-1} (\mathbf{P}_{p|p} - \Phi_p \mathbf{P}_{p-1|p-1} \Phi_p^T + \Delta \mathbf{x}_p \Delta \mathbf{x}_p^T) \quad (10)$$

where $\mathbf{P}_{i|j}$ is the error covariance at step i given the measurements up to step j , Φ_p is the state transition matrix, $\Delta \mathbf{x}_p$ denotes the post-fit state residuals at time step p , and N is the length of the sliding window which in this work is set to 30. In the presence of measurement outages, the corresponding time steps are excluded from the summation. As outages may affect individual spacecraft independently, the empirical covariance—and thus the adaptation—must be performed separately for each satellite.

Compared to the baseline EKF, the adaptive architecture introduces no modifications to the measurement model or state definition, acting exclusively through the online estimation of the dynamical process noise covariance.

SIMULATION SETUP AND RESULTS

Simulation Environment

This section presents the simulation environment used to assess the performance of the proposed relative navigation algorithms. The navigation algorithms are evaluated using a high-fidelity simulation environment developed in MATLAB[®] and Simulink[®].¹⁵ This environment propagates the spacecraft states and generates the reference trajectories, whereas the GNSS raw measurements are

simulated using the in-house GEMS software tool, which generates realistic GPS and Galileo observables by modelling the principal measurement error sources and perturbations, including ionospheric delay, satellite and receiver clock offsets, broadcast ephemeris errors, and receiver noise.¹⁶

As described in the Relative Navigation Filter section, the filter receives as input the commanded thrust computed by the control system. However, the actual thrust may differ due to actuation errors and noise. It is therefore necessary to model these uncertainties in order to assess the capability of the navigation filter to cope with them. In this work, individual thruster dynamics are not explicitly simulated; instead, their aggregate effect on the overall thrust is modelled, following the work of Scala.²

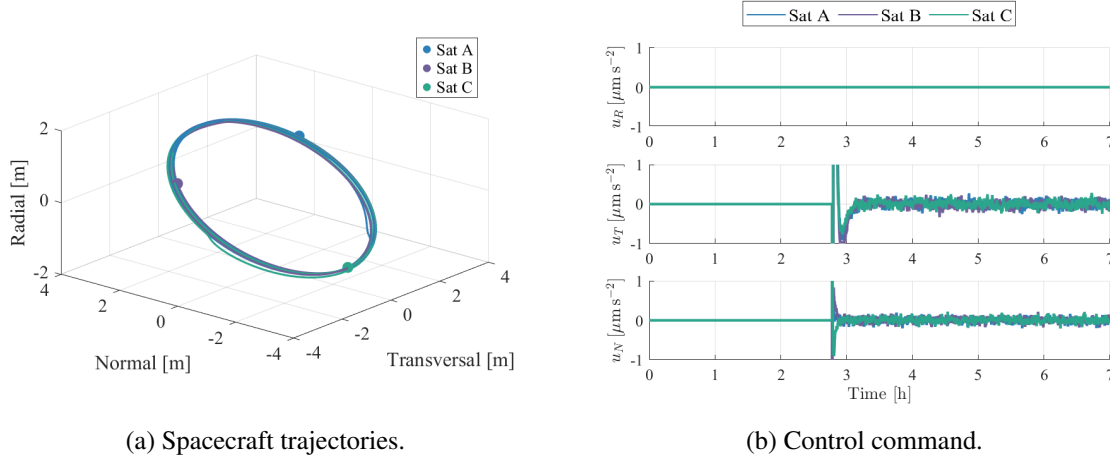


Figure 1: Formation maintenance of TriHex (scientific phase).

Table 1: Initial filter settings.

Parameters	Value	Parameters	Value
<i>Process noise parameters</i>		<i>Initial state uncertainties</i>	
σ_N [cycles]	0.1	σ_r [m]	1000
$\sigma_{N_{SD}}$ [cycles]	0.05	σ_v [m/s]	1
h_0 [s]	$3 \cdot 10^{-24}$	$\sigma_{a_{emp,R}}$ [nm/s ²]	2500
h_{-2} [s]	$2 \cdot 10^{-21}$	$\sigma_{a_{emp,N}}$ [nm/s ²]	5000
<i>Measurement noise std dev</i>		$\sigma_{a_{emp,T}}$ [nm/s ²]	1875
σ_p^{GAL} [m]	0.3	$\sigma_{\delta t}, \sigma_{\delta t_{rel}}$ [m]	10^6
σ_p^{GPS} [m]	0.6	$\sigma_{\delta t}, \sigma_{\delta t_{rel}}$ [m]	10^5
σ_ϕ^{GAL} [m]	0.002	σ_N [cycles]	10^6
σ_ϕ^{GPS} [m]	0.002	$\sigma_{N_{SD}}$ [cycles]	10^6

Table 2: Thrusting noise and errors.^{2, 17}

Parameters	bEKF	AEKF
$\sigma_{a_{emp,R}}$ [nm/s ²]	3750	750
$\sigma_{a_{emp,T}}$ [nm/s ²]	5000	1000
$\sigma_{a_{emp,N}}$ [nm/s ²]	2500	500

Table 3: Lower and upper bounds for the least-squares minimisation.

Parameters	Value
σ_l [nm/s ²]	$[365 \ 500 \ 250]^T$
σ_u [nm/s ²]	$[5625 \ 7500 \ 3750]^T$

Results and discussion

The proposed algorithms are evaluated using the formation-maintenance scenario of the TriHex mission concept.¹⁸ The study involves three spacecraft flying in a fixed triangular formation along a General Circular Orbit (GCO) with respect to a virtual chief in a Sun-Synchronous Orbit (SSO) at an altitude of approximately 500 km. The inter-satellite distance is 5 m (centre-to-centre), as shown in Figure 1a, highlighting the need for highly accurate and robust relative navigation. The control

Table 4: Initial relative orbital elements with respect to virtual satellite for the TriHex formation maintenance scenario.

Relative orbital elements	Satellite A	Satellite B	Satellite C
Relative semimajor axis ($a\delta a$) [m]	0.00	0.00	0.00
Relative mean longitude ($a\delta \lambda$) [m]	0.00	0.00	0.00
Relative eccentricity ($a\delta e_x$) [m]	-0.72	-0.72	1.44
Relative eccentricity ($a\delta e_y$) [m]	-1.25	1.25	0.00
Relative inclination ($a\delta i_x$) [m]	2.17	-2.17	0.00
Relative inclination ($a\delta i_y$) [m]	-1.25	-1.25	2.50

acceleration to maintain the spacecraft in the fixed triangular configuration is applied only in the transversal and normal directions (Figure 1b) to reduce the overall amount of required delta-v during science phase.^{2,19} The simulation begins with the spacecraft following their natural dynamical evolution. After an initial uncontrolled phase, the formation-maintenance controller is activated.

In this scenario, the performance of a baseline Extended Kalman Filter (bEKF) is compared with that of the adaptive filtering approach introduced in this work (AEKF), with initial filter settings valid for both scenarios summarised in Table 1. Instead, Table 2 contains the initial values assigned to the process noise standard deviations for the empirical accelerations components based on the type of filter. Note that the bEKF needs higher process noise values, and this is because with smaller values the filter experiences convergence issues and therefore it is not able to provide a relative navigation solution. This is not the case for the AEKF which is able to converge independently from the initial process noise values. Finally, the lower and upper bounds for the least-squares minimisation used in the ADMC are reported in Table 3 and the initial relative orbital elements with respect to the virtual satellite for each of the three spacecraft are shown in Table 4.

Table 5: RMSE for relative navigation during formation maintenance.

Parameters	bEKF	AEKF
r_R [mm]	1.29	0.95
r_T [mm]	0.70	0.53
r_N [mm]	0.43	0.36
v_R [$\mu\text{m/s}$]	26.70	13.81
v_T [$\mu\text{m/s}$]	18.57	9.90
v_N [$\mu\text{m/s}$]	11.51	8.40

Table 6: Maximum magnitude of the error at control activation for formation maintenance.

Parameters	bEKF	AEKF
r_R [mm]	5.94	8.25
r_T [mm]	9.44	20.67
r_N [mm]	1.07	1.07
v_R [$\mu\text{m/s}$]	130.93	138.40
v_T [$\mu\text{m/s}$]	645.16	996.08
v_N [$\mu\text{m/s}$]	37.01	34.60

Table 5 reports the root mean square error achieved by the two filtering approaches during active formation maintenance. All filters achieve millimetre-level relative positioning accuracy, largely owing to the very short inter-satellite distances, which significantly reduce the effect of differential error sources, including orbital perturbations and ionospheric delays. Slightly worse performance is obtained with the bEKF, primarily due to the higher process noise required to ensure filter convergence and the correct fixing of the single-differenced ambiguities.

It is also instructive to analyse the filter behaviour at the instant the formation-maintenance controller is activated. At this point, the spacecraft are required to acquire and maintain the prescribed relative geometry, resulting in a sudden increase in the control acceleration, as shown in Figure 1b. This transient affects the navigation solution, temporarily degrading the estimation accuracy, as can be observed in Figures 2a and 2b. The corresponding peak navigation errors are reported in Table 6.

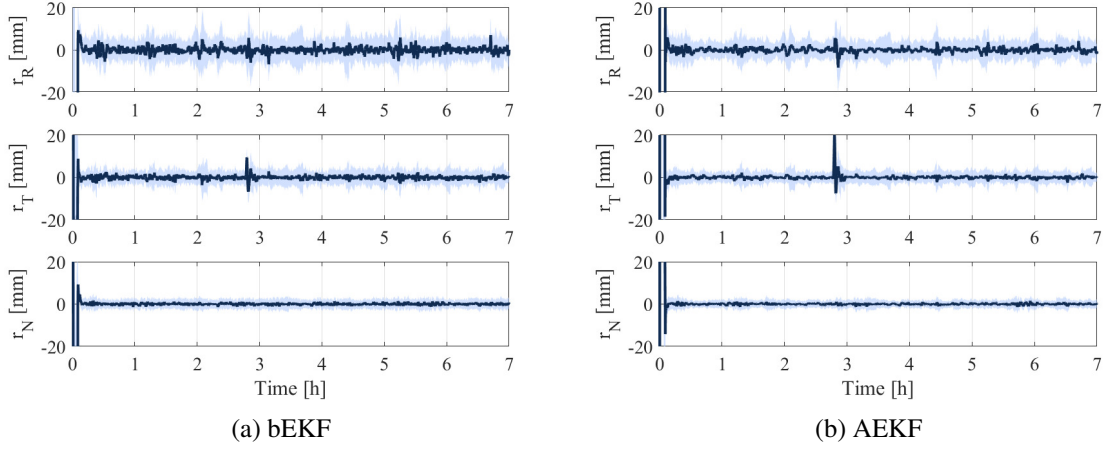


Figure 2: Relative position estimation error. The shaded area represents the estimated $\pm 3\sigma$ covariance bounds.

The smallest peak error is achieved by the bEKF. This behaviour is a direct consequence of its larger process noise, which enables the filter to more readily accommodate rapid changes in the spacecraft dynamics induced by the onset of thrusting. On the other hand, the AEKF exhibits the largest transient error. This can be explained by the adaptation mechanism itself. Prior to control activation, the adaptive filter tunes the process noise based on the unmodelled perturbing accelerations acting on the spacecraft. As a result, the estimated process noise may be relatively low when the controller is activated. When formation maintenance begins, the thrust acceleration increases almost instantaneously, whereas the process noise adaptation requires time to respond, as it relies on the empirical covariance estimate computed over the sliding window defined in Eq. 10 and on the smoothing factor in Eq. 9. Consequently, the filter cannot immediately adjust its process noise to reflect the new dynamical conditions, leading to a temporary degradation in estimation performance.

CONCLUSIONS

This paper investigated the feasibility of GNSS-based autonomous relative navigation for very-close formation-flying missions in Low Earth Orbit subject to continuous low-thrust actuation. Particular attention was devoted to metre-level formations, where stringent navigation and safety requirements demand highly reliable onboard state-estimation capabilities.

To this end, a GNSS-based relative navigation architecture employing single-differenced carrier-phase measurements was developed and assessed. An Adaptive Extended Kalman Filter, based on the ADCM framework, was implemented and compared against a conventional Extended Kalman Filter (bEKF). The adaptive approach allows online estimation of the process noise associated with the dynamical states while preserving consistency with the underlying spacecraft dynamics. The proposed algorithms were evaluated in a representative formation-maintenance scenario derived from the TriHex mission concept, involving three spacecraft flying with inter-satellite distances of approximately 5 m under continuous control. In both cases, millimetre-level relative positioning accuracy was achieved, largely thanks to the short inter-satellite baselines, which significantly reduce differential perturbations and GNSS error sources. The results show that the main advantage of the adaptive approach lies in its increased robustness during filter initialisation. In particular, the AEKF

successfully converged even when the initial process-noise levels were insufficient for the bEKF to reliably converge and correctly fix the single-differenced carrier-phase ambiguities. Once steady-state operation was reached, however, the adaptive estimation of the process noise provided only limited improvements in navigation accuracy. Nevertheless, the demonstrated robustness makes adaptive filtering a valuable option for close-proximity formation-flying missions operating under uncertain dynamical conditions.

Future work should investigate the impact of attitude determination errors on the navigation solution and assess the proposed algorithms in a broader range of operational scenarios, including formation reconfiguration manoeuvres and other control-intensive formation-flying activities. Such analyses would further build upon the preliminary feasibility assessment presented in this work.

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