Collaborative Navigation – Using Relative Sensor Measurements to Aid and Synchronize the Absolute Navigation of Swarm Members

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ABSTRACT

A method is presented to synchronize and aid the absolute navigation solutions of the members of a swarm by means of relative inter-swarm measurements. Moreover, the operational benefits thereof are discussed.

Collaborative operation of vehicles, especially of unmanned aerial vehicles in close formation, requires accurate relative and absolute navigation. A novel method for collaborative multi-sensors fusion of relative and absolute navigation information is presented designed to cope with GNSS-denied environment.

Relative inter-swarm measurements and absolute navigation means cannot be fused straight away as they are defined in fundamental different frames. Moreover, the sensor fusion has to fulfil two objectives – firstly, restoring the relative geometry of the swarm, and secondly, determining the absolute positions of each vehicle in an optimal way for the overall swarm.

Key for collaborative navigation is to establish a common knowledge within the swarm which is achieved by exchanging the absolute state estimations, the state uncertainties and the relative measurements. Based on the common knowledge the "Consistent INS Drift Algorithm" computes for each vehicle a new position which is statistically optimal for the overall swarm. Simultaneously, these new positions represent the actual geometry of the swarm by essentially resampling the relative measurements. By fusing these new positions the navigation filters are synchronized and the relative measurements are implicitly used to aid the absolute navigation solutions.

This reveals several operational benefits: the absolute navigation solutions are consistent – the whole swarm drifts consistently as only the Inertial Navigation Systems (INS) may remain as absolute navigation means, and hence, the naming "Consistent INS Drift Algorithm". Moreover, the drift is statistically slower than the best individual INS. Having at least one vehicle equipped with a drift-free navigation mean such as Terrain Referenced Navigation stops the swarm to drift. Therefore, heterogeneous navigation systems are natively supported enabling true collaboration.

1.0 INTRODUCTION

The Future Combat Aircraft System (FCAS) will start soon the next phase of its development. The aim of its development is a 6^{th} generation fighter alongside unmanned remote carriers (RC) as well as a combat cloud (CC) in a system-of-systems approach. All assets of FCAS will be networked to share and gain an overall situational awareness of the battlespace and to cooperatively execute missions such as cooperative engagement. A key element for collaborative mission execution, yet underestimated, is to know the position of the assets performing jointly a task.

Current navigation systems rely largely on Global Navigation Satellite Systems (GNSS) such as GPS for precise navigation. However, it is likely to encounter GNSS-jamming and even GNSS-spoofing in the mission area making precise navigation information unavailable. Cooperative mission execution and especially formation flight requires consistent absolute position estimations and/or relative position estimation of the involved assets which can be addressed only partly by GNSS-denied navigation methods.

In the remainder of this paper the Collaborative Navigation is presented which is designed to provide the members of a swarm with consistent absolute navigation estimations also under GNSS-denied conditions. Firstly, the architecture of the Collaborative Navigation is introduced. Afterwards the core of the Collaborative Navigation, the so-called “Consistent INS Drift Algorithm” is presented. Finally, the interaction between the Main Filter of the Collaborative Navigation and Consistent INS Drift Algorithm is discussed and topped off with simulation results.

2.0 COLLABORATIVE NAVIGATION

2.1 Problem Description

As stated in the introduction the swarm members performing collaboratively a task such as emitter localization or formation flight require precise absolute navigation information as well as precise relative estimations w.r.t. the other swarm members.

It is important to understand the environmental/operational conditions under which the Collaborative Navigation shall work: as mentioned in the introduction GNSS-denial is likely to be encountered in the mission area making a convenient source for precise navigation information unavailable. GNSS-denied navigation methods may not be sufficient in terms of availability, continuity, integrity and relative accuracy to allow for instance formation flight. Therefore, relative measurements are required to ensure consistent absolute state estimation with the method as presented in this paper. Additionally, stealth requirements may prohibit or limit the use of active sensors such as radars for GNSS-denied navigation or for relative measurement within the swarm. Finally, the datalink which has a central function for the Collaborative Navigation by exchanging navigation information may be jammed or may be subject to emission control for the sake of low observability.

2.2 Collaborative Navigation Architecture

Figure 1 illustrates the architecture of the Collaborative Navigation. The architecture can be decomposed in four major functional blocks.

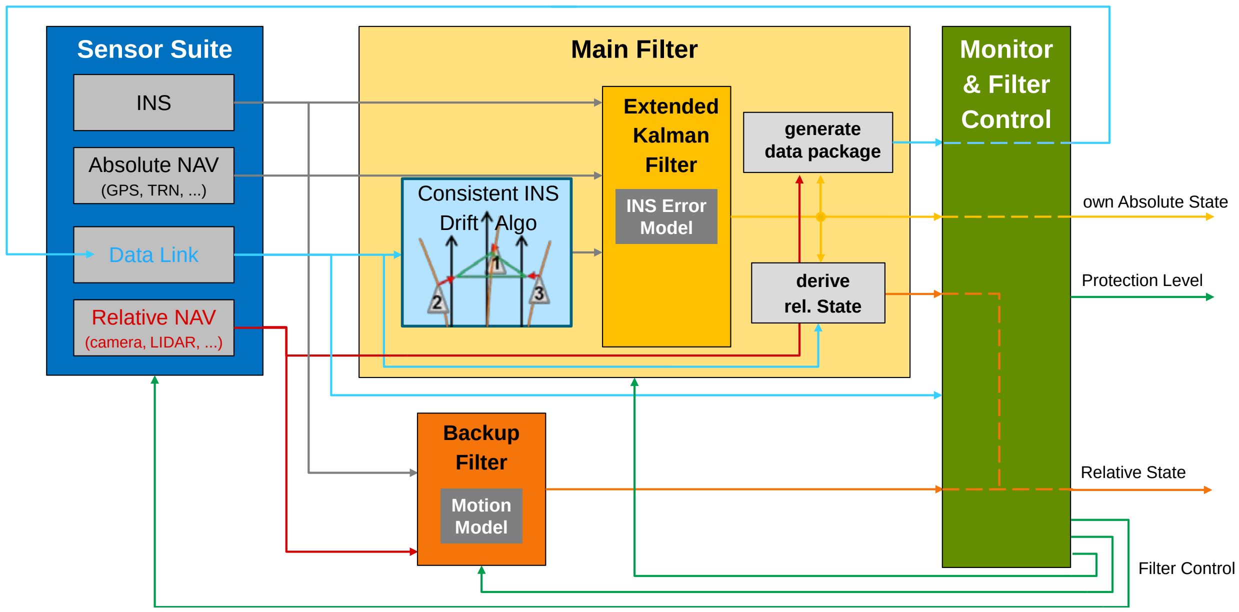

Figure 1: Collaborative Navigation Architecture

The *Sensor Suite* contains the navigation sensors of a traditional aircraft such as Inertial Navigation System (INS) and Global Navigation Satellite System (GNSS) or other absolute navigation means such as Terrain Referenced Navigation (TRN). Moreover, the Sensor Suite of the Collaborative Navigation is equipped with relative navigation sensor such as camera or LiDAR and a datalink which is not part of a classical navigation system. The relative navigation sensor is required to provide information about the relative position/velocity/attitude of the other swarm members. Note that the datalink is not a sensor itself but it is required to exchange navigation information between the swarm members in order to create a common knowledge within the swarm. Note that not all platforms of the swarm need to be equipped with the "full" sensor suite which is demonstrated later.

The *Main Filter* is an Extended Kalman Filter (EKF) formulated in the error state space and provides the absolute state estimation (position, velocity and attitude) and according covariance of the own platform. The Main Filter fuses INS and GNSS or other absolute navigation means (e.g. TRN) as well as the relative navigation information via the Consistent INS Drift Algorithm (see chapter 2.3). Additionally, relative navigation information are derived by subtracting the absolute state estimations of the own platform from the other swarm members which have been received via the datalink. The focus of the paper is on the Main Filter alongside the Consistent INS Drift Algorithm.

The *Backup Filter* works fully autonomously and does not rely on any external systems / sources such as GNSS or datalink. The Backup Filter is essentially a tracking filter to track the other swarm members and provide relative position and velocity estimation thereof. As the name indicates the Backup Filter is required as backup for the Main Filter in case that the datalink and GNSS are unavailable. In case of unavailability of the datalink while GNSS may still be available the relative estimations of the Backup Filter are used to monitor the required separation between swarm members while the Guidance-Navigation-Control (GNC)-

loop can be still closed using the absolute state estimation of the Main Filter.

The *Monitor and Filter Control* consolidates the outputs provided by the Main Filter and the Backup Filter and performs according moding in case of a detected fault in one of the filters or the "environmental conditions" such as loss of datalink requires an adaption. Figure 2 summarizes the moding of the Collaborative Navigation based on the environmental / operational conditions w.r.t. availability of GNSS and datalink.

	GNSS available	GNSS-denied environment
Data link available	Good absolute and relative position accuracy	Relative position accuracy is maintained. Absolute navigation solution will drift as INS drifts. At least one formation member is required with an alternative absolute navigation mean such as TRN to maintain absolute position accuracy of the entire formation
Data link not available (e.g. due to required stealth or jamming)	Fly in formation based on absolute position* In close formation, GNSS errors, such as ionospheric or tropospheric ones, cancel out → use same satellites (e.g. ensured by mission planning)	Sensor Fusion of relative and absolute position not feasible. However, graceful degradation of "old" navigation solutions after entering this mode

Main Filter

Backup Filter

Figure 2: Environmental / Operational Conditions and modes of Collaborative Navigation

2.3 Consistent INS Drift Algorithm

The Consistent INS Drift Algorithm (CIDA) is the heart of the Collaborative Navigation. The Consistent INS Drift Algorithm allows the fusion of the relative navigation information with the absolute navigation information. The CIDA resolves the issue that the absolute and relative navigation information are defined in two fundamental different frames. The absolute navigation information refers in some way to the earth frame, while the relative information refers to the other swarm members, and hence, to a moving frame for which the absolute state (e.g. position and velocity) is only known by means of state estimations which may have significant error especially in context of GNSS-denial.

The key idea of CIDA is to compute the positions, or more generally the states, of all members of the swarm in order to correctly reconstruct the relative measurements within the swarm or in other words to reassemble the swarm geometry as sensed by the relative sensors. This requires a common knowledge within the swarm which is achieved by exchanging the absolute state estimation and according covariance as well as the relative sensor measurements and measurement uncertainty of all swarm members. As there is an infinite number to reconstruct the swarm geometry, additionally the constraint of optimality is introduced such that overall absolute state estimation error of the swarm is minimized.

Figure 3 depicts the working principle of the Consistent INS Drift Algorithm with three swarm members depicted as grey triangles with solid lines for last iteration and with a dashed line for the current time step. The black lines show the ground truth while the orange lines represent the absolute state estimations (without absolute navigation means other than the INS in this example, and hence, the position estimate drifts). The principle can be split in four steps:

- a) relative measurements between swarm members are performed (depicted as green line) and exchanged between the swarm members
- b) the absolute state estimations and according covariance are exchanged between the swarm members, and hence, a common swarm knowledge has been created. The expected relative measurements are computed (shown as purple line) according to absolute state estimations of the

swarm members using an appropriate measurement equation $h(\cdot)$.

- c) the innovation depicted as red arrows are computed which is the core of the Consistent INS Drift Algorithm. The CIDA solves essentially a linear system of equations for the innovation (e.g. position innovation) of all swarm members simultaneously based on the common swarm knowledge. The derivation of the linear system of equation is presented after. The innovation is computed in such a way that updated state estimations of step d)
- d) [the updated state estimations] represent the relative measurements, and additionally, the state estimations are optimal meaning that the overall absolute error of the entire swarm is minimized. Note that state update (e.g. position update) is performed in the Extended Kalman Filter of the Main Filter rather than in predictor-corrector scheme as depicted in Figure 3.

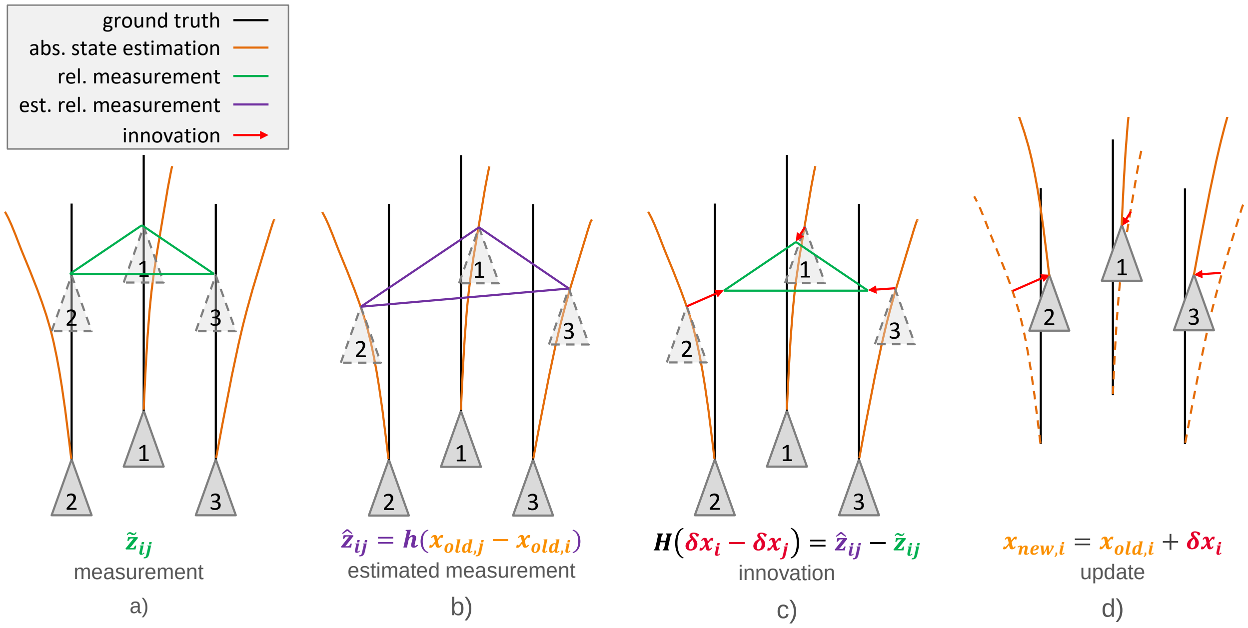

Figure 3: working principle of the Consistent INS Drift Algorithm

Below the linear system of equations, which is solved by the CIDA to obtain the innovation (e.g. position innovation), is derived. The fundamental equation of the CIDA expresses that the new state estimations shall reconstruct the relative measurements:

$$\tilde{z}_{ij} \approx h\left(x_{new,j} - x_{new,i}\right) \tag{1}$$

$$\tilde{z}_{ij} \approx h\left(\left(x_{old,j} + \delta x_j\right) - \left(x_{old,i} + \delta x_i\right)\right) \sim h\left(x_{old,j} - x_{old,i}\right) + H_{ij}\left(\delta x_j - \delta x_i\right) \tag{2}$$

$$H_{ij} := \left.\frac{\partial h(x)}{\partial x}\right|_{x = x_{old,j} - x_{old,i}} \tag{3}$$

whereas $\tilde{z}_{ij}$ represent the relative measurement between swarm member "i" and "j", $x_{new,i}$ describes the new state estimation of i-th swarm member which shall be computed by the CIDA and analogous $x_{old,i}$ describes the state estimation of the i-th swarm member before the CIDA computation. $h(\cdot)$ is called the measurement equation and computes the expected measurement based on the absolute state estimations. δx_i is the innovation such that $x_{new,i} = x_{old,i} + \delta x_i$. Moreover, H_{ij} is the Jacobian of the measurement equation which is also known as observation matrix in the context of Kalman filtering.

Equation **(2)** can be solved for $H_{ij}(\delta x_i - \delta x_j)$:

$$H_{ij}(\delta x_i - \delta x_j) = h(x_{old,j} - x_{old,i}) - \tilde{z}_{ij} = \tilde{b}_{ij} \quad \textbf{(4)}$$

by considering the permutations of i and j a linear system of equations is created of the following form:

$$H\delta x = b \quad \textbf{(5)}$$

Whereas

$$H = \begin{bmatrix} \mathrm{H}_{12} & -\mathrm{H}_{12} & 0 & \cdots \\ \mathrm{H}_{13} & 0 & -\mathrm{H}_{13} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \quad \textbf{(6)}$$

$$\delta x = [\delta x_{12} \quad \delta x_{13} \quad \cdots]^T \quad \textbf{(7)}$$

$$b = \left[h(x_{old,2} - x_{old,1}) - \tilde{z}_{12} \quad h(x_{old,3} - x_{old,1}) - \tilde{z}_{13} \quad \cdots\right]^T \quad \textbf{(8)}$$

The linear system of equations **(5)** cannot be solved uniquely as for instance the whole swarm can be shifted in position and still reproducing the relative geometry, respectively the relative measurements of the swarm members. The constraint reads that the weighted sum of innovations shall be zero:

$$W_Q^{-1} \sum_{i=1}^{n} Q_i^{-1} \delta x_i = 0 \quad \textbf{(9)}$$

With Q_i being the weight and denoting the covariance of the innovation δx_i and n denoting the number of swarm members. The normalization term is defined as follows:

$$W_Q = \sum_{i=1}^{n} Q_i^{-1} \quad \textbf{(10)}$$

As the innovation represents essentially the correction of the state estimation error, the criterion can be interpreted that the weighted sum of corrections, and hence, the according errors (e.g. drift of the inertial navigation systems) cancel each other out. Since this criterion ensures to obtain an overall statistical optimal solution for the swarm, it is also called *optimality criterion*. Another geometrical interpretation of the optimality criterion **(9)** is that the weighted center of the swarm does not change. This makes sense as the relative measurements do not contain any information form the “outer world”, and hence, cannot cause the swarm center to shift. Note that the movement of the swarm members is already correctly captured by inertial navigation systems (including other absolute navigation means if available). That the weighted swarm center does not change can be mathematically shown:

$$W_Q^{-1}\sum_{i=1}^{n} Q_i^{-1}x_{new,i} = W_Q^{-1}\sum_{i=1}^{n} Q_i^{-1}(x_{old,i}+\delta x_i) = W_Q^{-1}\sum_{i=1}^{n} Q_i^{-1}x_{old,i} + \underbrace{W_Q^{-1}\sum_{i=1}^{n} Q_i^{-1}\delta x_i}_{0}$$
$$W_Q^{-1}\sum_{i=1}^{n} Q_i^{-1}x_{new,i} = W_Q^{-1}\sum_{i=1}^{n} Q_i^{-1}x_{old,i} \quad (11)$$

Figure 4 illustrates a case study of the Consistent INS Drift Algorithm with five swarm members. The plot of the swarm can be interpreted as a full graph with the nodes being the swarm members. The grey graph represents the ground truth, the yellow graph represents the position estimation before the CIDA update ($x_{old,i}$) while the wine red graph represents positions computed by the CIDA ($x_{new,i}$). In this case study swarm member #1 has a small position standard deviation while the remaining swarm members have a ten times higher position standard deviation causing the swarm center to be located very closely to swarm member #1. The CIDA solution matches very well with the ground truth. This case study shows already one major property of the Consistent INS Drift Algorithm, and hence, of the Collaborative Navigation. The highly accurate position information from swarm member #1 is spread to the remaining swarm members such that their absolute position error is largely reduced.

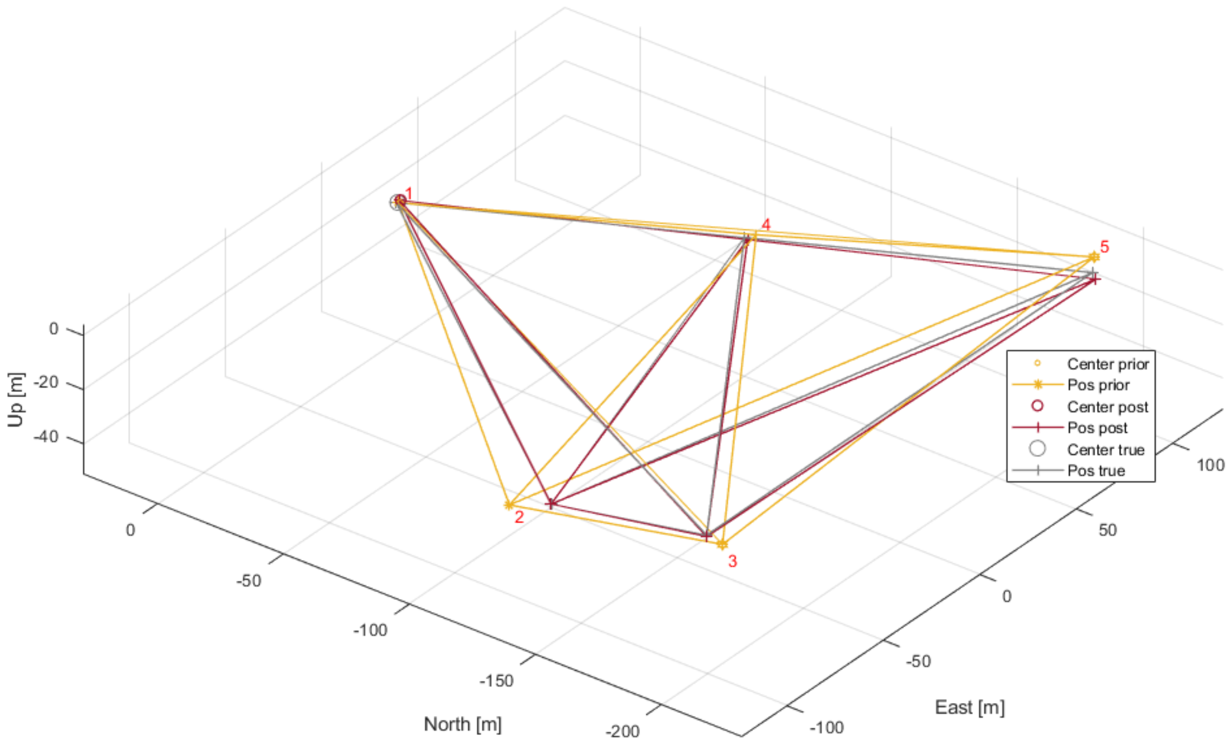

Figure 4: Result of the Consistent INS Drift Algorithm

2.4 Interaction of Consistent INS Drift Algorithm and Main Filter

In the previous chapter the Consistent INS Drift Algorithm has been introduced and first properties of the CIDA have been revealed. This chapter discusses the interaction of the CIDA and the Main Filter.

The Main Filter is an Extended Kalman Filter aiding the drifting Inertial Navigation System (INS) with the other on-board absolute navigation means such as GNSS as well as the position output of the CIDA. The CIDA is executed on all swarm members with the very same input data (common swarm knowledge). The common swarm knowledge includes the absolute state estimation along its covariance as well as all relative measurements of all swarm members.

Fusing the position output of the CIDA in absolute navigation filter has two implications. Firstly, the relative measurements are effectively used to aid the drifting INS. Secondly, the absolute state estimations of the swarm members become "synchronized" and are consistent as they reassemble the relative inter-swarm measurements as per the design of the CIDA.

This reveals several operational benefits/interesting use cases. Before discussing these advantages, the term "implicit relative navigation accuracy" is introduced which denotes the relative accuracy between the absolute state estimations of two swarm members. In contrast the "explicit relative accuracy" refers to the accuracy of the explicitly computed relative state estimation (e.g. by explicit subtraction of the absolute state estimations or by directly estimating the relative states as done by the Backup Filter). Below some interesting uses cases are selected:

- Datalink available & no drift-free absolute navigation mean available within swarm:

  In the following considered case the datalink is available to exchange the navigation information as required by the CIDA. However, there is no absolute navigation mean except the inertial navigation systems available. In such a situation the absolute state estimations of the swarm members are ongoing consistent meaning that the relative error remains constant although the absolute state estimation errors increase as the inertial navigation systems drift. Finally, the overall swarm drifts, however statistically slower than the best individual INS / filter solution while the relative accuracy is maintained. This property was the origin of the naming for the "Consistent INS Drift Algorithm".

- Datalink available & at least one drift-free absolute navigation mean available within swarm:

  In case that at least one swarm member has an absolute navigation mean besides the INS such as Terrain-Referenced Navigation (TRN) or Vision-based Navigation (VBN) available, the whole swarm benefits and the absolute state estimations of all swarm members are long-term stable.

- Heterogonous navigation systems of swarm members / extreme case "blind" swarm member:

  The Collaborative Navigation does not take any assumption on the navigation equipment. Therefore, swarm members with heterogeneous navigation systems are natively supported. In the extreme case some swarm members may be "blind" meaning that they are not equipped with sensors to obtain relative measurements or may be unable to generate these relative measurements e.g. due to sensor failures. Nevertheless, the minimum number of independent relative measurements must be respected such that the linear system of equations of the CIDA is not under-determined.

  One use case of a swarm with heterogeneous navigation systems is a swarm of light UASs for which some UASs may be equipped with a specialized navigation system while the remaining UAVs may be equipped with the bare minimum to save SWaP (Size Weight and Power) for mission equipment for instance. The minimum equipped platforms benefit of the ones with specialized navigation equipment, and hence, the herein presented Collaborative Navigation allows for true collaboration.

To make full advantage of the Collaborative Navigation the users of the Collaborative Navigation require an according design. The most prominent user is the Formation Manager which is in charge of the generation and the execution of collision-free trajectories for formation flight. By closing the Guidance-Navigation-Control (GNC) loop via the absolute state estimation, each swarm member can fly along the planned trajectory without the need to consider the other swarm members in the flight control law as long as each swarm member remains in its flight corridor. If every swarm members remain in their corridor can be monitored via the relative state estimations. The relative estimation can be either obtained from the Backup-

Filter or Main Filter derived from the absolute state estimations.

Figure 5 depicts the true (solid line) and estimated (dashed line) trajectories of a simulation scenario consisting of five swarm members. Each swarm member has an initial navigation error of 100 m. Swarm members #1 and #4 have GPS available while the remaining swarm members have no GNSS nor alternative absolute navigation means except the INS available. The swarm joins after approximately 50 s a fixed formation.

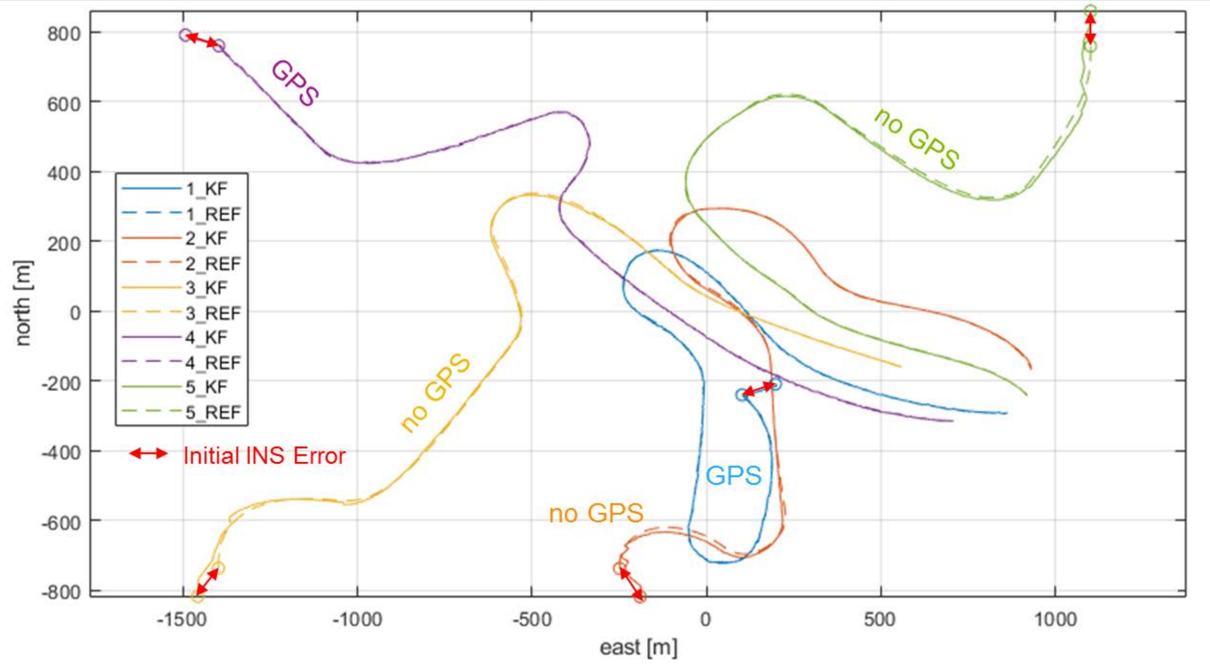

Figure 5: Main Filter

The upper row of Figure 6 shows the relative error of the absolute state estimation of the Main Filter. The lower row shows the true absolute distance between the swarm members in the north and east direction. The initial relative errors decrease quickly in the horizontal plane and go below 5 m after the swarm members have joined a fixed formation at around 50 s.

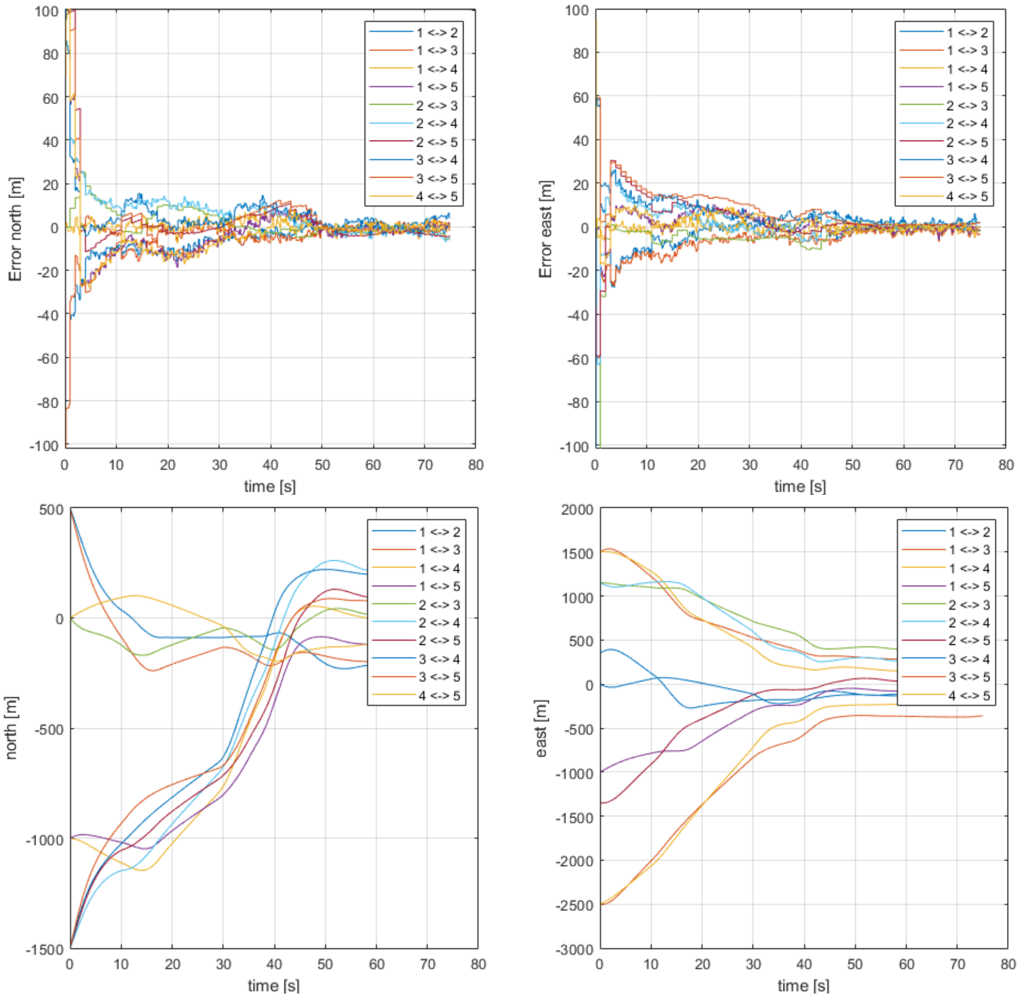

Figure 6: Relative Accuracy of Main Filter

As an example the absolute position error of swarm member #2 is illustrated in Figure 7. Although swarm member #2 is not equipped with any absolute navigation means except an INS, the absolute position error in the north and east axis decreases quickly and reaches less than 10 m. This simulation scenario presents how the overall swarm benefits if at least one swarm member has an absolute drift-free navigation mean available.

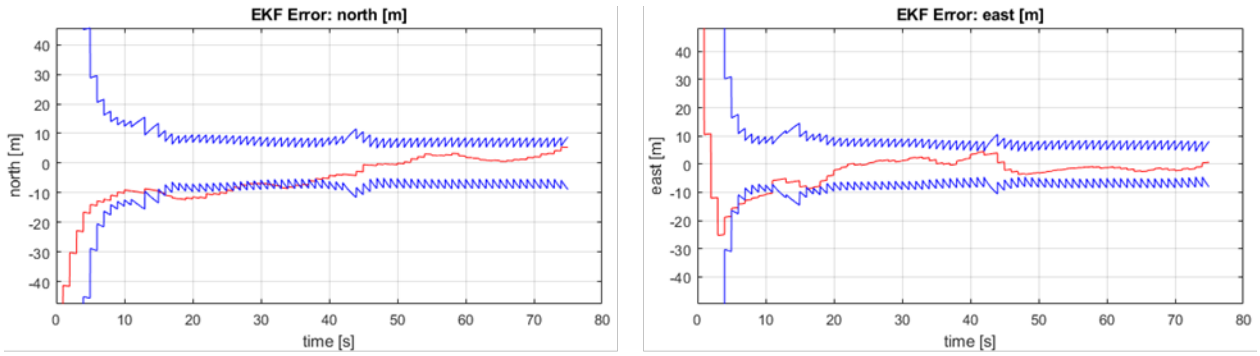

Figure 7: Absolute Navigation Error of Swarm Member #2 (no absolute navigation means available)

3.0 SUMMARY

Cooperative tasks of the Future Combat Aircraft System (FCAS) require precise absolute and relative position and velocity estimation. The assets of FCAS will likely encounter GNSS-jamming or GNSS-spoofing in the mission area making a precise navigation source unavailable. However, GNSS-denied navigation methods alone are only partly solution to that since they cannot fulfil the required relative accuracy, availability, continuity and integrity of the cooperative tasks, especially of the safety-critical formation flight. The Collaborative Navigation is presented which provides the swarm members with consistent absolute state estimations. Consistent absolute state estimations mean that they are of high relative accuracy also during GNSS-denied conditions. Heart of the Collaborative Navigation is the "Consistent INS Drift Algorithm" (CIDA). By exchanging the absolute state estimations and according covariance as well as the relative measurements within the swarm a common swarm knowledge is created. Based on this common swarm knowledge the CIDA computes for each swarm member a new position and/or velocity which reconstructs the relative measurements and is optimal for the overall swarm. Due to the optimality criterion it can be mathematically shown that the overall swarm drifts slower than the best individual INS / navigation solution. The Main Filter of Collaborative Navigation fuses the inertial navigation system (INS) with the position and/or velocity of the CIDA and other absolute navigation means if available. Therefore, relative measurements are used to aid the INS, and moreover, the absolute state estimations of the swarm members are consistent among themselves. The paper concludes with the simulation results showing how swarm members without absolute navigation means except the INS benefit from swarm members having an absolute navigation mean available. This proves that native support of heterogeneous navigation systems allowing for true collaboration.