# Distributed Visual Sensing and Fusion for Advanced Air Mobility

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***Abstract*—Surveillance solutions for Advanced and Urban Air Mobility frameworks are a key factor to enable safe operations of highly automated aircraft in the civil airspace. To design solutions suitable for all types of aircraft, non-cooperative sensors can be used, though many challenges arise when the small dimensions of the vehicles and their proximity to the ground during low-altitude missions are considered. A distributed sensing concept can be efficiently applied to address these challenges by exploiting multiple sensors within a surveillance network. This paper proposes a strategy to fuse the information collected by three ground-fixed cameras within a network of multiple distributed sensors and is tested with during experimental flight tests. The solution exploits standalone tracking estimates of each camera within a fusion center that performs triangulation and three-dimensional tracking. This approach is tested in a scenario involving two small UAVs flying at low altitude. The paper deals with the challenges of associating the two objects from independent and unrelated tracks to achieve robust triangulation, which produces meter-level mean errors with respect to GNSS-based ground truth.**

***Keywords—Advanced Air Mobility, Visual Localization, Unmanned Aerial Vehicles, Sensor Fusion, triangulation***

## I. Introduction

The increasing worldwide urbanization process, the development of the smart cities vision and the technological advancements in the field of autonomous aircraft, e.g., Uncrewed Aerial Vehicles (UAVs) and Electrical Vertical Take-Off and Landing (eVTOL), all generated a radical shift in the conceptualization of the urban and regional transportation modes with higher requests for sustainable and on-demand choices. In this novel scenario, Advanced Air Mobility (AAM) and Urban Air Mobility (UAM) can be viewed as key players, complementing private and public ground transport by occupying the vertical dimension and exploiting highly automated aircraft. Recent studies have remarked that AAM air taxis can potentially compete with the conventional ground transport modes during short-distance travels, i.e., under 40 km [1], and enhance connectivity in areas where such modes lack or are less efficiently provided [2]. The on-demand, fast and flexible nature of UAM services can also contribute to applications that require a short response time. As pointed out in [3], such applications are perceived as more useful by the public. As an example, the study discussed in [4] highlights the opportunity of improving emergency medical services in remote areas using AAM technology to replace ground ambulances, while reference [5] suggests that drone-aided delivery services can improve the healthcare environment of rural areas.

The interest for UAM/AAM transportation solutions is increasing yearly, as witnessed by forecasts in reference [6], which estimates that up to 100 cities will have UAM operations in 2050. However, the realization of such a radical shift in the daily lives of the modern population needs to pass through major development and testing phases, which are still on-going. These not only include regulatory efforts towards the definition of the environment, which requires standardization between the different stakeholders, but also technological investigations ranging from infrastructure-based architectures, sustaining large volumes of operations, and aircraft-based ones. Specifically, one of the key points to be addressed is the design of surveillance strategies to effectively integrate novel platforms in the airspace. Conversely to the conventional surveillance strategies used for manned aircraft, these novel solutions need to cope with smaller form factor platforms needing to be detected and their low-altitude mission profiles, both representing open challenges.

In this context, the use of non-cooperative sensors to detect all types of aircraft, either equipped with onboard transponders or not, within a network of distributed sensing nodes [7] is regarded as a promising solution to enable continuous and accurate awareness of the air traffic. The researchs centered around this focal point are investigating different sensing sources and their fusion. In works such as [8], the use of RADAR sensors to achieve accurate distance information of low altitude flying targets is demonstrated. However, the occurrence of RADAR interference when multiple devices operate at short distances, as discussed in [9], can potentially jeopardize the surveillance performance. This issue can be solved exploiting passive sensors such as visual cameras whose advantageous size, weight and power budgets make them a suitable choice for both ground and airborne installations. References such as [10-13] discuss different strategies to detect small UAVs with a single monocular camera by applying Machine Learning approaches [10-11] or combinations of frame differencing, morphological filtering and optical flow

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[12-13]. These solutions show good detection performance but lack distance estimations, which are of paramount relevance for the surveillance framework, where full three-dimensional localization of targets is desired. This latter aspect can be counteracted by applying visual-based distance estimation strategies as discussed in references [14] and [15] which rely on a priori information on the target, either given by onboard markers [14] or by the knowledge of its physical dimension [15]. If ground-based cameras are considered, an alternative solution can then be found in the use of triangulation techniques relying on the information retrieved by at least two cameras. References [17] and [18] discuss this type of implementation starting from a simulation environment [17] and extending to a real flight scenario where four cameras are used to track and triangulate one small UAV during a low altitude flight [18]. Both works highlight the improved accuracy achieved in the tracking estimate when more than two cameras are used to triangulate the location of the UAV.

In this paper a similar approach is followed and a visual-only surveillance strategy for the UAM environment is proposed, exploiting a centralized fusion architecture. This involves independent detection and Kalman filter tracking threads for all cameras whose output is broadcasted to a fusion center, where triangulation of tracks is performed. With respect to works such as [17-18], the proposes strategy also involves a first solution to match the standalone firm tracks from each camera and avoid the generation of false tracks. This is highly needed in the considered scenario, becoming a requirement in high airspace density conditions, where multi-object tracking is performed. After triangulation, three-dimensional tracking is performed within the fusion center, yielding estimates of the position and velocity of the small UAVs. The developed strategy is tested on the data collected during flight field experiments with three ground cameras located in different spots of the testing facility and with different pointing directions. The cameras are used to detect and track two small UAVs flying on the same route. These experiments were carried out at the NASA's Langley Research Center during joint experimental activities between the NASA Revolutionary Aviation Mobility (RAM) subproject of the Transformational Tools and Technology (TTT) project and the NASA AAM project. Additionally, there was participation of the University of Naples "Federico II". The small UAVs used as sensing targets were operated during the NASA High Density Vertiplex (HDV) subproject [18].

The remainder of the manuscript is structured as follows. Section II describes the visual-only localization and tracking strategy, detailing the fusion architecture. Section III overviews the experimental setup used to collect data used for the paper. The results of the proposed solution are discussed in Section IV. Finally, section V draws the conclusion of this work.

## II. Visual Localization and Tracking Strategy

A schematic representation of the proposed fusion architecture is depicted in Fig. 1, where a number of *n* cameras is considered in the network; in the case under analysis *n*=3. The architecture consists of two main processing threads acting on the camera-level and on the Fusion Center-level.

### A. Local Camera Processing

Each camera independently performs detection and tracking on a local level. Specifically, the detection task ("Detector" block in Fig. 1) is carried out by applying a frame differencing strategy to localize moving objects on the image plane given the fixed cameras' position. The detections found at this stage are then fed to a linear Kalman filter tracker, which was introduced by the authors in reference [8]. The tracker foresees different stages through which detections, i.e., one plot tracks, are transformed into firm tracks by exploiting ad-hoc association criteria. The Euclidean distance between two consecutive detections (in pixels) is used to define a first criterion, namely setting a threshold ($d_{th}$) above which association is rejected to avoid tracking objects whose relative angular motion with respect to the camera is too fast to represent a small UAV during flight. The firm tracks collected by each camera contain information about the line of sights ($\boldsymbol{l}$) between the camera and the tracked object in terms of azimuth (*az*) and elevation (*el*) angles along with their rates. Such values are expressed in the North East Down (NED) reference frame centered at the camera location, yielding to the definition of vector $\boldsymbol{l}|_{cn}^{N}=[az, el]$ where the subscript refers to the *n*-th camera and the superscript refers to the NED frame.

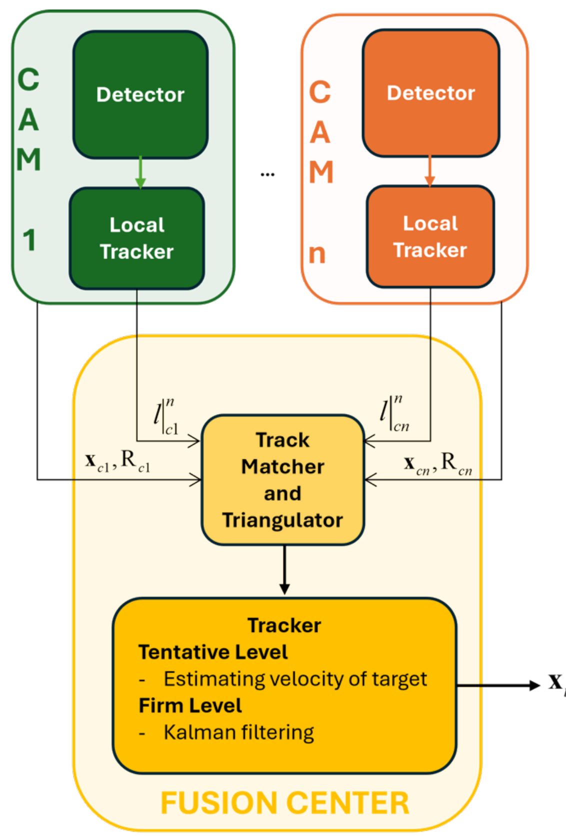


Fig. 1. Scheme of the proposed fusion solution accounting for *n* cameras (CAM) within the network.

### B. Fusion Center Processing

The camera-to-target line of sight information estimated by the firm tracking process of each camera in the network is shared with the Fusion Center where triangulation and tracking are performed. The former is carried out by also using the knowledge of the pose of each camera within the network, expressed in terms of its location and orientation with respect to a NED frame with origin in a fixed world point, thus defining the World Reference Frame (WRF). If the $n$-th camera of the network is considered, these quantities are defined as vector $\mathbf{x}_{cn}$ and matrix $R_{cn}$ respectively. The latter is a parametrization of the 3-2-1 Euler angles rotation from the camera reference frame to the NED one. The triangulation block estimates the three components of the position of each target ($x_t$, $y_t$, $z_t$) in the WRF using a linear triangulation method from [19] and implemented using high level MATLAB functions. The output of the triangulation block is the measurement vector $\mathbf{z}_t=[x_t, y_t, z_t]$ which is fed to a linear Kalman filter acting as tracker at the Fusion Center level; in absence of triangulation measurements, the tracks are propagated by predicting the targets' state with a nearly-constant-velocity model up to a maximum time span ($t_{max}$) after which they are deleted. The output of the tracker block is a state vector $\mathbf{x}_t=[x, y, z, \dot{x}, \dot{y}, \dot{z}]$ which contains the position ($x$, $y$, $z$) and velocity ($\dot{x}$, $\dot{y}$, $\dot{z}$) of the triangulated targets with respect to the WRF origin. Since no velocity measurement is available, the Fusion Center tracker starts with a Tentative Level where the position difference between two consecutive triangulated points is used to initialize the three velocity components of the targets. Once available, a tentative track is directly transformed into a firm track where the state of each target is predicted and corrected using Kalman filtering. At firm tracking level, association is performed to distinguish between the tracks of the different UAVs, which are the targets of the proposed sensing strategy. This is achieved by exploiting the Mahalanobis distance.

Before passing triangulated measurements to the tracker, a matching strategy between the firm tracks retrieved by the cameras in the network is used to avoid generating false tracks from mismatches. To highlight the need for such matching strategy, Fig. 2 depicts a common occurrence where two cameras are tracking the same target (UAV 2) but only one camera is tracking the other target (UAV 1). This situation yields two possible triangulated points: a correct one, using the line of sight between CAM 2 – UAV 2 and CAM 1 – UAV 2, depicted with the unit vectors $\mathbf{u}|^{n}_{c2\text{-}UAV2}$ and $\mathbf{u}|^{n}_{c1\text{-}UAV2}$, respectively, and a virtual one using the mismatch between $\mathbf{u}|^{n}_{c2\text{-}UAV2}$ and $\mathbf{u}|^{n}_{c1\text{-}UAV1}$. To discard such virtual points, the combinations of all available firm tracks from different cameras are used to generate a set of possible triangulated point candidates. These are then compared to the previous estimate of the tracker ($\mathbf{x}_{t|k-1}$) to compute their velocity between the two time instants. If such velocity exceeds a pre-defined threshold, which can be set accordingly to local flight area regulations, the points are discarded. This velocity-based strategy can be decoupled for the horizontal and vertical directions of motion to be more adherent with the dynamics of multirotor platforms, thus setting a threshold $v_{H,th}$ and $v_{V,th}$ for the maximum horizontal and vertical velocities, respectively.

The matching strategy is also used in cases where one firm track is retrieved by each camera. When all $n$ cameras in the network declare one or more firm tracks the matching strategy is slightly changed. First, the velocity-based check procedure is applied on all the points triangulated using the whole set of cameras. Then, if no match is found, the procedure is repeated using all the possible combinations of points achieved using two-cameras triangulation.

The matching strategy proposed in this paper relies on the availability of a previous knowledge on the location of the tracked objects in the WRF. In the absence of such knowledge, as it happens during initialization of the Fusion Center tracker, a different strategy should be used. Among the possible solutions, one could potentially use available a priori information about the allowable distances and velocities in the flight area to identify matches between different visual tracks and begin triangulation. However, in this case, high density flights operations occurring on similar trajectories and with similar velocities represent a highly challenging scenario. Indeed, passive shape-based ranging information could also be exploited to match the different tracks, though the uncertainty in the distance estimates increases with the distances reached by the targets, yielding to an unbalanced trade-off between correct and false matches. The initialization of three-dimensional tracks from visual tracks matches is thus still an open point which is not addressed in this work, where the Fusion Center's tracks are assumed to be already initialized.

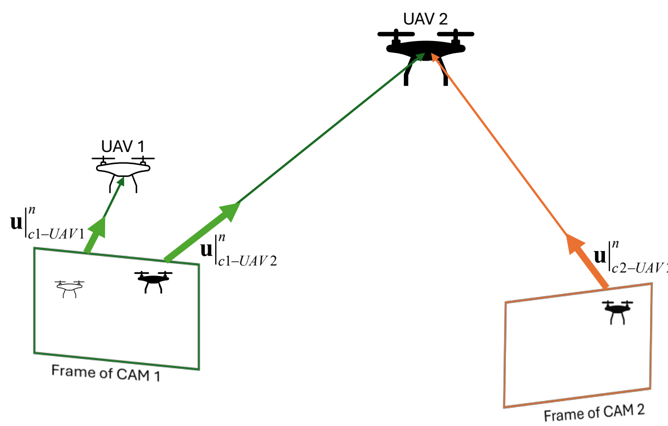


Fig. 2. Graphic representation of a scenario where matching of firm tracks is required. Only one UAV is tracked by both cameras.

## III. Experimental Setup

The data used in the framework of this manuscript were collected during one day of field tests performed at the City Environment Range Testing for Autonomous Integrated Navigation (CERTAIN) range flight testing facility at NASA Langley. During the tests, three ground-based sensing nodes equipped with RADARs, visual cameras and Global Navigation Satellite System (GNSS) receivers and patch antennas were used to record the flight of two small UAVs operating for the HDV project. The nodes are shown in their respective location in Fig. 3. The *Rooftop* node was mounted on top of a building rooftop approximately 10 meters above ground, the *Gantry* node was mounted on the gantry structure at about 60 meters from ground and the *Wythe creek* node was installed on the ground. In the context of this paper, only the cameras installed on each node are considered. To ease the reading of the manuscript, the cameras are referred to as C1, C2 and C3 for *Rooftop*, *Gantry* and *Wythe creek*, respectively. The three cameras on each node have the same resolution of 4096x3000 pixels each.

The location of the three cameras is visualized on the satellite map of Fig. 4, where their Field of View (FOV) and the origin of the WRF are also depicted. The FOV of cameras C1 and C3 have the same extensions, about 63° x 48° in the horizontal and vertical directions, respectively, while camera C2 has a slight smaller FOV of about 47° x 36°. The trajectory flown by the two UAVs (labeled using their tail tags: N556NU and N561NU) is also shown in Fig. 4.

The UAVs used during flight are two Alta 8 platforms manufactured by Freefly seen in Fig. 5 prior to flight. During flight, the UAVs reached a maximum distance of about 1 kilometer from all the cameras in the network.

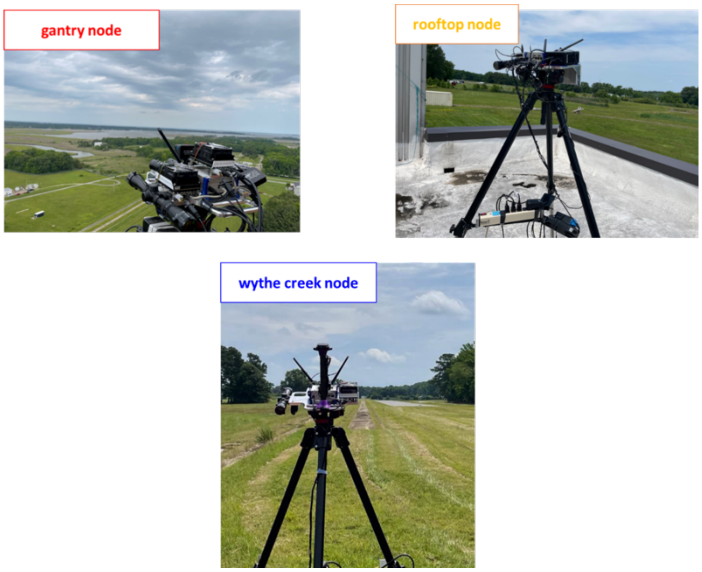


Fig. 3. Snapshots of the sensing nodes in their respective locations during experimental activities.

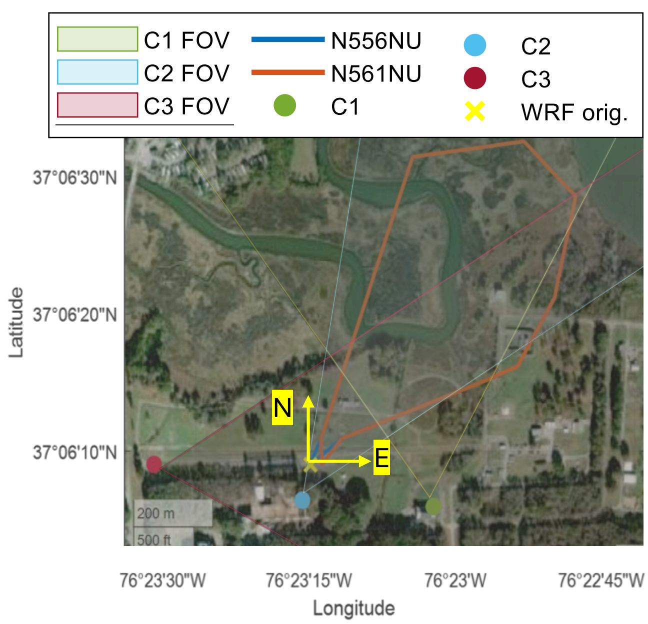


Fig. 4. Satellite map for experimental setup.

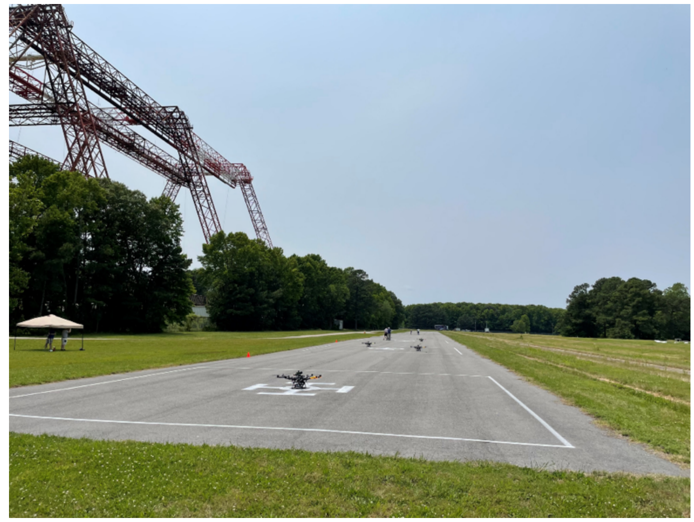

Fig. 5. Alta-8 UAVs before flight during one of the field tests.

## IV. Experimental Results

### A. Local Cameras Tracking

The results achieved with the visual local trackers are shown and discussed in this section. Specifically, the local trackers exploit a distance $d_{th}$=15 pixels for local detection-to-track association. The plots in Fig. 6 to 8, for camera C1, C2 and C3 respectively, show the time variation of the firm tracking estimated azimuth and elevation for both UAVs (labeled as "FT") and their Ground Truth ("GT"). The latter is computed using the GNSS positioning information logged by the onboard autopilot and the GNSS positioning information logged by the receiver installed on each node. As expected, all three cameras are able to continuously track the objects except when either occluded or not in the FOV. In the case of camera C1 (Fig. 6), the two UAVs appear to be completely untracked in the time span from 230 seconds to 340 seconds for aircraft N556NU and 280 seconds to 400 seconds for aircraft N561NU during which they exit the horizontal FOV of the camera, shown in Fig. 4.

Results on camera C2 (Fig. 7) also show a similar trend. In this case, the longest track interruption occurs in the time span between 200 seconds and 250 seconds when the platforms reach azimuth values larger than 55°. In the case of camera C3 (Fig. 8), instead, the longest track interruption in the whole network is verified and lasts about 200 seconds. This again occurs as the UAVs, during the returning leg of their trajectories, move at azimuth values exceeding the dimension of the camera's FOV, around 65° while considering the relative pointing direction.

The frequent occurrence of track interruptions is an undesirable effect for the triangulation-based strategy, which requires firm tracks from at least two cameras to locate the targets in the WRF. The geometric configuration of the camera network favors a continuous observation of the UAVs, deployed on this specific trajectory, when moving from one camera to another. This is more easily seen in Fig. 9 where the number of camera ($n_{cam}$) tracking the two UAVs at each time is presented showing very few instances of three cameras tracking the same target, but very consistently tracked by one camera the majority of the time.

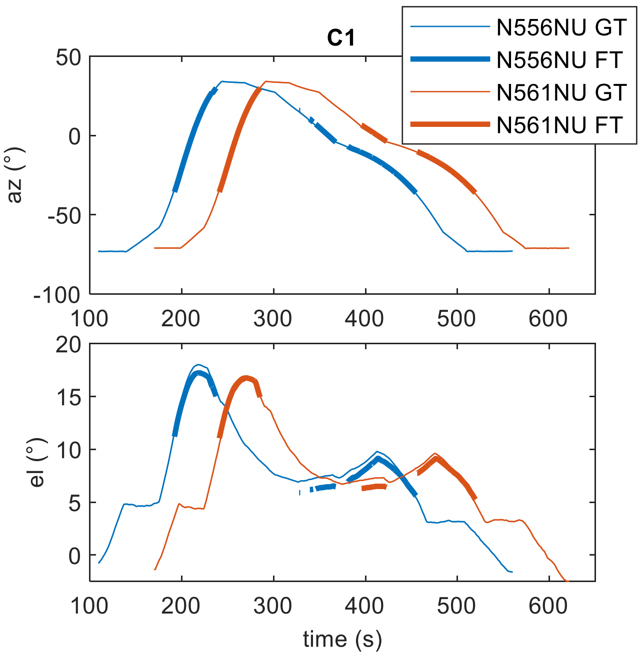


Fig. 6. Visual tracking results on camera C1.

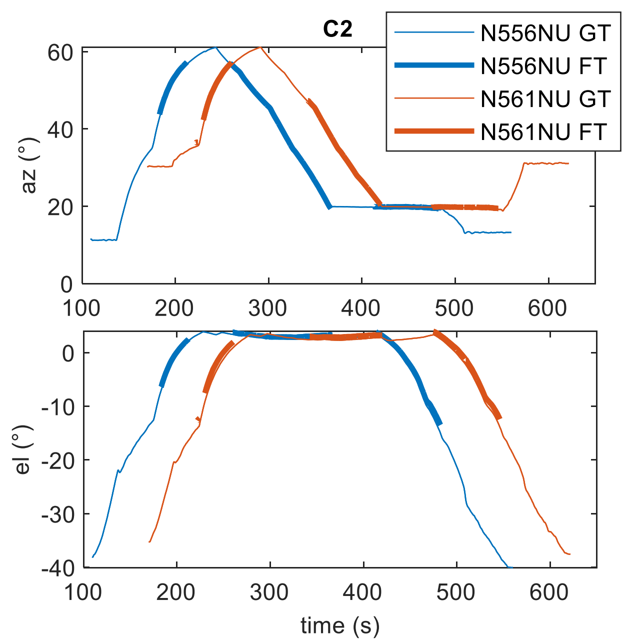


Fig. 7. Visual tracking results on camera C2.

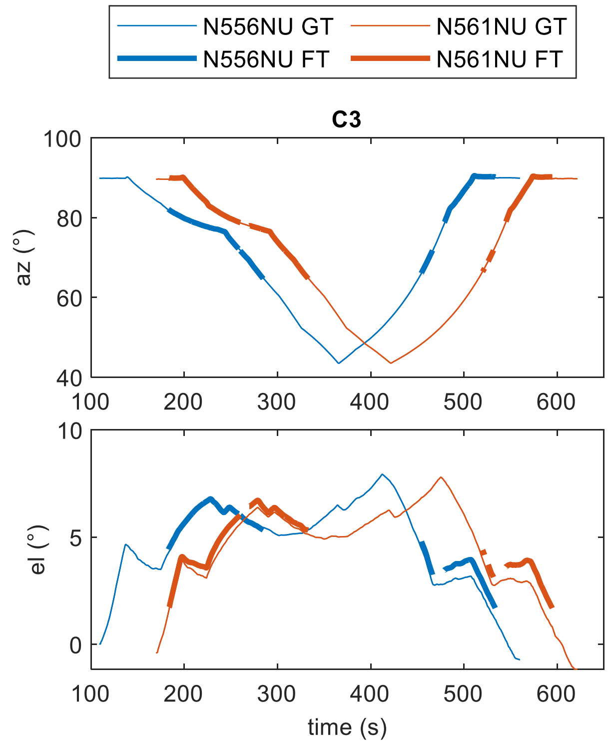


Fig. 8. Visual tracking results on camera C3.

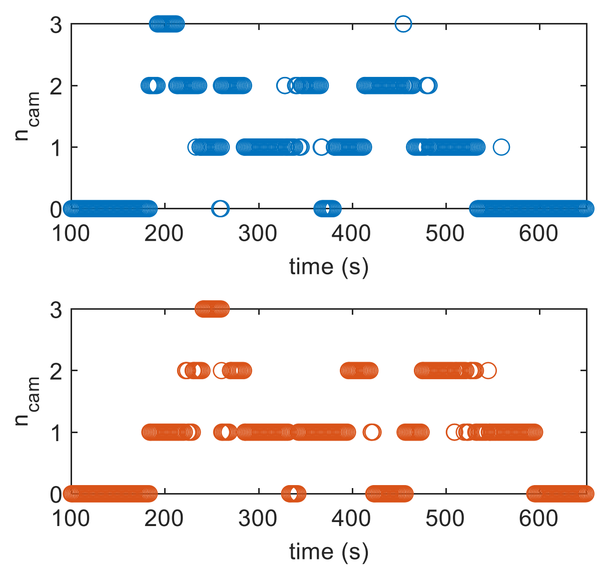


Fig. 9. Number of cameras tracking N556NU (top) and N561NU (bottom) during time.

### B. Fusion Center Tracking

To produce correct matches between the firm tracks of different cameras, the thresholds of $v_{H,th}$=20 m/s and $v_{V,th}$=10 m/s are considered. The results are shown in Fig. 10 where the

GT (identified with the thin lines in the figure) is considered with respect to the origin of the WRF. The three-dimensional tracks collected by the Fusion Center, based on triangulation of the firm tracks from the cameras' in the network, are depicted with thicker lines. The plots show the expected results in terms of coverage, which are mostly due to the disposition of cameras within the network. Dropouts in the tracks follow the trend depicted in Fig. 9 with interruptions occurring whenever the number of tracking cameras drops below one. The prediction only procedure carried out by the Fusion Center prolongs the duration of tracks of the UAVs even during the lack of triangulation measurements for a maximum time of $t_{max}$ = 1 second after which tracks are deleted. The longest track interruptions occur when the UAVs are out of the FOV of camera C3 and start being tracked by cameras C1 and C2 only. However, when C1 starts losing tracks, in the timespan around 300 seconds and 400 seconds, a complete loss of information is verified, with only few recoveries occurring when the maximum distance of about 740 meters from the origin of the reference is reached. Although interruptions are highly frequent, the coverage over the trajectory of the two UAVs achieved with the proposed triangulation and tracking method is as high as 98%. Such percentage is computed by summing up the instances in which both a three-dimensional firm track and its corresponding GT are present while the number of tracking cameras is $n_{cam} \geq 2$, thus making triangulation possible.

Performance-wise, the tracks exhibit meter-level mean error with a trend increasing with the distance of the targets from the cameras, as noticeable in Fig. 11 where the errors of the tracking estimates with respect to the GT are reported. Specifically, the East and North track components show the larger errors reaching values about 35 meters and 65 meters for the case of N556NU, respectively. Such values are achieved when the UAV is at the maximum distance from the WRF origin (about 900 meters) and result from the prediction of its tracks.

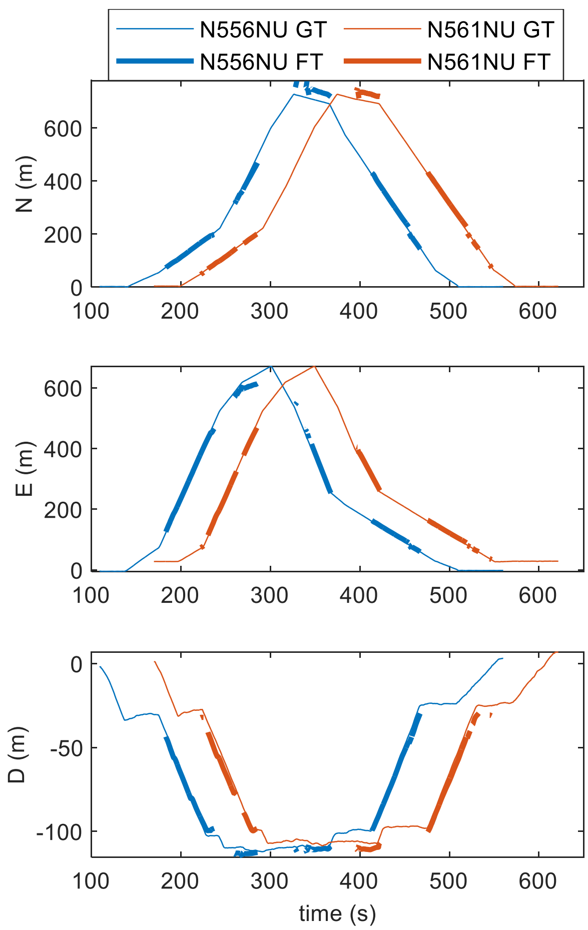

Fig. 10. Fusion Center tracking results based on triangulation of visual cameras firm tracks.

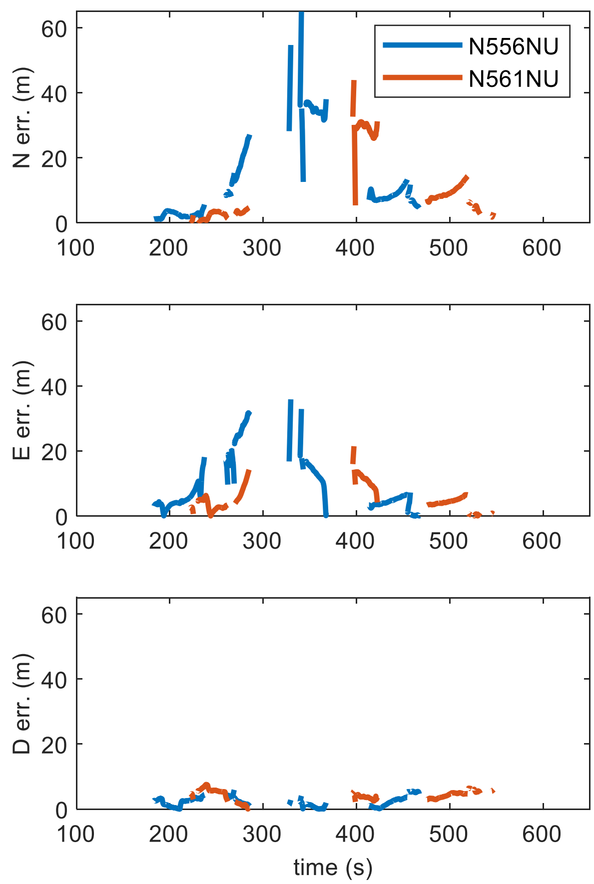


Fig. 11. Errors of Fusion Center tracking based on triangulation of visual cameras firm tracks.

## V. Conclusion

In this paper a triangulation-based fusion solution for a set of three ground-based cameras is proposed and tested as a distributed sensing surveillance strategy for the operation concepts of Urban and Advanced Air Mobility. The solution utilizes the firm tracking estimates retrieved by independent processing threads, which act locally at each camera. Such tracks are shared with a Fusion Center within a centralized fusion scheme, where they are used to estimate the three components of the position of each tracked object in the world, thus overcoming the lack of distance estimates, which is a common obstacle for single-camera sensing architectures. The outcome of the triangulation procedure is then used by a tracker that propagates the retrieved information in time. The paper proposes a preliminary strategy to match the firm tracks retrieved by the different cameras to avoid the generation of false tracks from virtual targets. The solution shows encouraging results when applied to data collected during field tests with two small UAVs, achieving meter-level average errors though the geometrical disposition of cameras does not provide the needed minimum number of tracks for triangulation with the desired frequency. Interesting conclusions can be drawn from the application of the proposed strategy to the available experimental data. As a first consideration, the need for a matching strategy which is challenged by the highly similar appearance of the two targets and their similar flight pattern is a challenging issue and will require further investigation in different directions. The availability of an independent ranging sensor, such as the RADAR, can undoubtedly play a crucial role in this context and its implementation in the sensing algorithm will yield the design of a final fusion solution where each sensor in the network can provide its estimates and contribute to the retrieval of an optimal state of each target. Yet, if visual-only distributed sensing solutions are to be sought, single-camera passive ranging approaches providing a coarse distance information to be confirmed with the use of the other cameras over time is a feasible alternative. Furthermore, considering the current structure of the fusion algorithm proposed in this paper, the association between the firm track of a single camera with an existing three-dimensional track generated by the Fusion Center is a solution which will be investigated further to promote a more continuous coverage of the surveillance volume.

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