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Target localization with a distributed Kalman filter over a network of UAVs

Salvatore Bassolillo[1,a], Egidio D'Amato[2,b], Massimiliano Mattei[3,c], Immacolata Notaro[1,d] *

[1]Department of Engineering, University of Campania "L. Vanvitelli", 81031 Aversa, Italy

[2]Department of Science and Technology, University of Naples "Parthenope", Napoli, Italy

[3]Department of Electrical Engineering and Information Technology, University of Naples "Federico II", Napoli, Italy

[a]salvatorerosario.bassolillo@unicampania.it, [b]egidio.damato@uniparthenope.it, [c]massimiliano.mattei@unina.it, [d]immacolata.notaro@unicampania.it

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Abstract. Unmanned Aerial Vehicles (UAVs) have gained significant usage in various kinds of missions, including reconnaissance, search and rescue, and military operations. In rescue missions, timely detection of missing persons after avalanches is crucial for increasing the chances of saving lives. Using UAVs in such scenarios offers benefits such as reducing risks for rescuers and accelerating search efforts. Employing a formation of multiple drones can effectively cover a larger area and expedite the process. However, the challenge lies in achieving autonomous and scalable systems, as drones are typically operated on a one-to-one basis, requiring a large team of rescuers. To enhance situational awareness and distribute communication load, this paper proposes a decentralized Kalman filtering algorithm that exploits sensor data from multiple drones to estimate target positions and support guidance and control algorithms. The algorithm combines Consensus on Information and Consensus on Measurements techniques. Preliminary validation is conducted through numerical simulations in a sample scenario.

Introduction

In recent decades, the use of UAVs (Unmanned Aircraft Vehicles) has experienced exponential growth in both civil and military sectors. The widespread adoption of these aircraft can be attributed to their ease of use and versatility in various missions. However, in certain scenarios, a single UAV may not suffice, and a collaborative team of UAVs is preferred. Such formations offer comparable or even greater mission capabilities, along with improved flexibility and robustness [1]. According to the Center for Research on the Epidemiology of Disasters (CRED) [2], the issue of fatalities and disappearances due to natural events remains a significant concern globally. To mitigate risks for human rescuers, UAVs should be prioritized for initial rescue operations in hazardous environments. Collaborative efforts among multiple drones have garnered attention from researchers in recent years, as they provide an effective solution to expedite the search process [3]. The coordination and collaboration of UAVs are crucial to function as a unified entity, maintaining formation and directing their flight toward the target.

In this paper, a distributed estimation algorithm for a formation of UAVs is proposed to locate a possible missing skier under the snow. The situational awareness is obtained by equipping UAVs with on-board heterogeneous sensors. The distributed algorithm is based on a decentralized Kalman filtering technique that involves a set of local Kalman filters, one for each UAV. By considering the formation as a network of vehicles, every node provides onboard sensors data and contributes to the estimation of the overall state [4]. With respect to a centralized architecture, running on a leader, that receives information from the other nodes, the decentralized scheme

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decreases the computational burden on the central node of the formation and it is less vulnerable against system failure, being not depending on a single aircraft.

The proposed sensor fusion algorithm receives measurements from a Global Positioning System (GPS) receiver and an Inertial Navigation System (INS), that represent the most widely used sensors for navigation purposes. To enhance system capabilities in hazardous environments and the robustness to sensors fault, each aircraft is equipped with a radio transponder to measure the relative distance between vehicles. Such device can be based on time-of-flight measurements over ultra-wideband radio signals or on the Received Signal Strength Indication (RSSI) of the same communication standard used to create the formation network. In order to find targets, each aircraft is equipped with a modern avalanche transceiver (ARTVA), typically used by back country skiers, whose signal power measurements, from multiple drones, can be used to perform triangulation and locate missed people.

Problem Statement

Let us consider a heterogeneous swarm of N UAVs, composed of aircraft in multi-rotor or fixed wing configurations. The swarm must survey a specific area in order to identify the presence of a snow-covered skier after an avalanche event. For first rescue mission in the search of a missing skier and for navigation purposes, UAVs must be able to estimate the position of the skier and their position in the airspace.

The discrete-time model of each UAV can be described in the inertial reference frame by the following equations:

$$\begin{cases} \boldsymbol{S_i}(k) = \boldsymbol{S_i}(k-1) + \mathbf{V}_i(k-1)T_s + \boldsymbol{\omega}_i^S(k) \\ \mathbf{V}_i(k) = \mathbf{V}_i(k-1) + \boldsymbol{\omega}_i^V(k) \end{cases} \quad \forall i = 1,2,\dots,N \tag{1}$$

where k is the time step, $\mathbf{S}_i(k) = [X_i(k), Y_i(k), Z_i(k)]^T$ is the vector of the spatial coordinates, $\mathbf{V}_i(k) = \left[V_{X_i}(k), V_{Y_i}(k), V_{Z_i}(k)\right]^T$ is the velocity vector of the i-th UAV, $\left[\boldsymbol{\omega}_i^{S^T}(k), \boldsymbol{\omega}_i^{S^T}(k)\right]^T$ is a process noise vector, and T_s is the sample time.

The global state vector $\mathbf{x}(k) \in \mathbb{R}^m$ is defined as:

$$\mathbf{x}(k) = [\mathbf{S}_1^T(k), \mathbf{V}_1^T(k), \dots, \mathbf{S}_N^T(k), \mathbf{V}_N^T(k), \mathbf{S}_t^T(k)]^T \tag{2}$$

where the position of the missing skier is identified by $\mathbf{S}_t(k) = [X_t(k), Y_t(k), Z_t(k)]^T$.

Each UAV is equipped with a set of sensors composed of:

- a GPS, to measure its position in the airspace;
- $N-1$ transponders, to evaluate the relative distance to each UAV in the swarm;
- an avalanche receiver antenna (ARTVA), to detect the signal from the skier avalanche transceiver.

Consider the measure provided by the GPS

$$\mathbf{z}_i^{GPS}(k) = [X_i(k), Y_i(k), Z_i(k)]^T + \boldsymbol{\nu}_i^{GPS}(k) \tag{3}$$

the measurement provided by the transponders

$$\mathbf{z}_i^{Tr}(k) = [d_{i1}(k), \dots, d_{iN}(k)]^T + \boldsymbol{\nu}_i^{Tr}(k) \tag{4}$$

and the measurement provided the ARTVA

$$\mathbf{z}_i^{AT}(k) = d_{it}(k) + \boldsymbol{\nu}_i^{AT}(k) \tag{5}$$

where $\boldsymbol{\nu}_i^{GPS}(k)$, $\boldsymbol{\nu}_i^{Tr}(k)$, and $\boldsymbol{\nu}_i^{AT}(k)$ are the corresponding sensor noises. The term $d_{ij}(k) = \left\|\mathbf{S}_j(k) - \mathbf{S}_i(k)\right\|_2$ represents the Euclidean between two aircraft, i and j, whereas $d_{it}(k) = \left\|\mathbf{S}_t(k) - \mathbf{S}_i(k)\right\|_2$ is the distance of the $i-th$ aircraft from the target skier, with $\|\cdot\|_2$ denoting the Euclidean norm.

The measurement vector of the overall set of sensors is represented by

$$\mathbf{z}_i(k) = \left[\mathbf{z}_i^{GPS^T}(k), \mathbf{z}_i^{Tr^T}(k), \mathbf{z}_i^{AT}(k)\right]^T + \mathbf{v}_i^T(k) \tag{6}$$

with $\mathbf{v}_i(k) = \left[\mathbf{v}^{GPS}{}_i^T(k), \mathbf{v}^{Tr}{}_i^T(k), \mathbf{v}_i^{AT}(k)\right]^T$ as the overall measurement noise vector.

Consensus Estimation

At any time k, the communication structure of the formation can be represented by an undirected graph $\mathbb{G}(k) = \{\mathcal{V}, \mathcal{A}(k)\}$, where $\mathcal{V} = \{1,2,\ldots,N\}$ is the set of UAVs, and $\mathcal{A}(k) \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges describing the communication link between the aircraft i and j. The i-th UAV can receive data from the j-th vehicle if the arc $(i,j) \in \mathcal{A}(k)$. For each aircraft i, $\mathcal{M}_i(k) = \{j: (i,j) \in \mathcal{A}(k)\}$ is the set of its neighbors, including the i-th vehicle, and $D_i(k) = card(\mathcal{M}_i(k)) - 1$ represents its degree, with $card(\cdot)$ representing the cardinality of a generic set.

Let $\xi_i(k)$ be the generic information associated with the $i-th$ agent. We assume that $\xi_i(k)$ is updated according to the Average Consensus Protocol [8]:

$$\xi_i^{(l+1)}(k) = \sum_{j\in A} W_{ij}(k)\xi_j^{(l)}(k) \qquad l = 0,1,\ldots,L-1 \tag{7}$$

performed on L consensus steps for each time instant k.

Coefficients $W_{ij}(k)$ can be computed using the Metropolis formula [9]:

$$W_{ij}(k) = \begin{cases} \frac{1}{1+max\{D_i(k),D_j(k)\}} & \text{if } j \in \mathcal{M}_i(k) \\ 1 - \sum_{j\in\mathcal{M}_i(k)} W_{ij}(k) & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

So that, to determine the weight, each agent i does not need any knowledge of the communication graph but only the degrees of its neighboring nodes, $D_j(k)$, with $j \in \mathcal{M}_i$.

The UAVs asymptotically reach the consensus if, for any initial condition $\xi_i^0(k)$, $\lim_{l\to\infty}\|\xi_i^l(k) - \xi_j^l(k)\| \to 0$, for each $(i,j) \in \mathcal{A}(k)$, where l is the generic consensus step.

Results

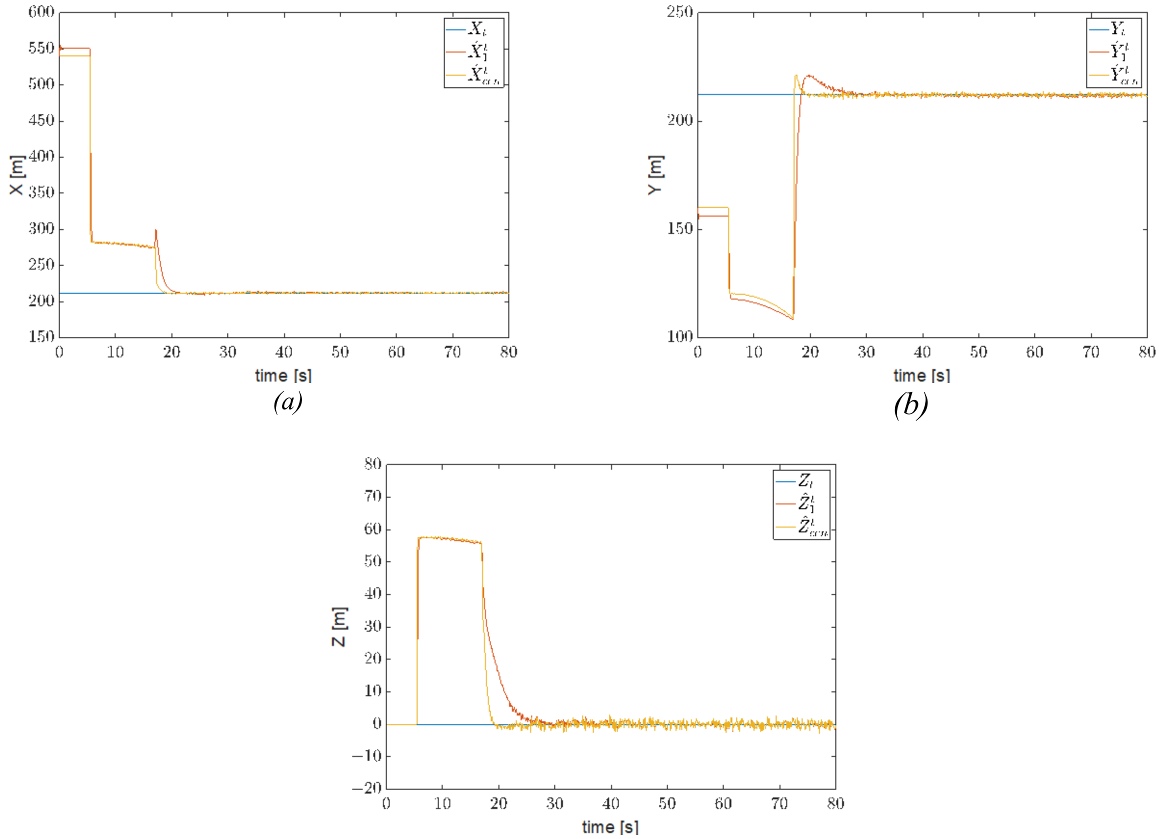
The performance of the proposed algorithm was evaluated by means of numerical simulations. As reference, a centralized version of the KF was considered, in order to verify the performance cost of the decentralized technique. In this section, to resume results, only an example scenario is considered, with a formation of 9 UAVs, flying together and surveying an area of interest to look for a target. Each aircraft flies along the same direction, at a constant speed of 5 m/s, with an altitude of 100 m above the terrain. Every agent is able to communicate with two neighbors, in order to form a cycle graph and it is equipped with an avalanche receiver to sense the signal from the target skier. Such receiver has a detection range of $d_{sens} = 200$ m.

At the beginning of the simulation, each aircraft knows only its position, initializing the overall state estimate with random values. Such assumption was useful to evaluate the convergence of the algorithm to the correct estimate and the ability to reach the consensus.

Fig. 1 show the estimated components of the target position vector, comparing the real value, the centralized IKF and the proposed decentralized KF. As shown in Figures, at the beginning of the simulation, the target position is still unknown being outside UAVs sensor range.

At $t = 5.5s$, the target enters in the sensor range of UAV_1, but it is not sufficient to be localized. Indeed, for localization problems using fusion algorithms, the measurements of at least three aircraft are required to effectively locate the target [5].

From $t = 17s$, the target is in the sensor range of UAV_1, UAV_2 and UAV_3 and it becomes localizable. The skier estimated position definitively converge at $t = 26s$.



(a) *(b)* *(c)*

Figure 1- Comparison of the estimates of the skier's coordinates: (a) x-component, (b) y-component, (c) z-component .

References

[1] F. Y. Hadaegh, S.-J. Chung, and H. M. Manohara, On Development of 100-Gram-Class Spacecraft for Swarm Applications, IEEE Systems Journal, vol. 10, no. 2, pp. 673–684, Jun. 2016. https://doi.org/10.1109/JSYST.2014.2327972

[2] D. Guha-Sapir, F. Vos, and R. Below, Annual Disaster Statistical Review 2011. 2012.

[3] L. Ruetten, P. A. Regis, D. Feil-Seifer, and S. Sengupta, Area-Optimized UAV Swarm Network for Search and Rescue Operations, in 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), Jan. 2020, pp. 0613–0618. https://doi.org/10.1109/CCWC47524.2020.9031197

[4] M. Cicala, E. D'Amato, I. Notaro, and M. Mattei, Scalable Distributed State Estimation in UTM Context, Sensors, vol. 20, no. 9, Art. no. 9, Jan. 2020. https://doi.org/10.3390/s20092682

[5] M. A. Azam, S. Dey, H. D. Mittelmann, and S. Ragi, Average Consensus-Based Data Fusion in Networked Sensor Systems for Target Tracking, in 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), Jan. 2020, pp. 0964–0969. https://doi.org/10.1109/CCWC47524.2020.9031250