



## Relative Navigation in UAV Applications

Tuncay Yunus Erkeç<sup>1</sup>, Chingiz Hajiyev<sup>2</sup>

<sup>1</sup>Turkish National Defense University, Hezarfen Aeronautics and Space Technologies Institute, Yeşilyurt/Istanbul  
tuncayyunus@gmail.com - 0000-0003-3357-0985

<sup>2</sup>Istanbul Technical University, Faculty of Aeronautics and Astronautics, Maslak/Istanbul 34469  
cingiz@itu.edu.tr - 0000-0003-4115-341X



### Abstract

This paper is committed to the relative navigation of Unmanned Aerial Vehicles (UAVs) flying in formation flight. The concept and methods of swarm UAVs technology and architecture have been explained. The relative state estimation models of unmanned aerial vehicles which are based on separate systems as Inertial Navigation Systems (INS)&Global Navigation Satellite System (GNSS), Laser&INS and Vision based techniques have been compared via various approaches. The sensors are used individually or integrated each other via sensor integration for solving relative navigation problems. The UAV relative navigation models are varied as stated in operation area, type of platform and environment. The aim of this article is to understand the correlation between relative navigation systems and potency of state estimation algorithms as well during formation flight of UAV.

### Keywords

Relative Navigation  
GPS  
Kalman Filters  
Unmanned Aerial Vehicles  
Localization

### Time Scale of Article

Received 6 October 2020  
Revised until 1 December 2020  
Accepted 5 December 2020  
Online date 30 December 2020

### 1. Introduction

Unmanned aerial vehicles (UAVs) have contributed great many to military force air domain especially for surveillance, reconnaissance, attack and defense missions. Besides, UAVs applications in the private sector other than military purposes plays an important role with regard to weather, human reconnaissance, forestry and agriculture [1], and photogrammetry beyond the capabilities of a manned aerial vehicles due to their low cost development and zero risk of loss of human life. However, operating a single drone is possible only in a limited area, therefore it is not effective compared with multiple drones on a mission. A new concept has come out since the air operations referred to more than one drone and it has been called Multi-UAV operations. These operations do not call for a change of performance of each drone yet allows them to perform an assigned mission through mutual cooperation in order to benefit the accuracy and efficiency that allows diversity [2].

Swarm UAV concept is used commercial area such petroleum and pipeline checking applications [3, 4], cargo applications [5] and also movie sector. The development of new relative navigation methods of UAV has a financial aspect. Because of these factors, lots of academic studies are focused on UAV formation subject [6].

Relative navigation is employed in separate platforms for rendezvous, formation flight, stereo imaging. The relative navigation aims UAVs well as terrestrial or naval autonomous vehicles [7, 8]. In this study, methods of UAVs formation flight methods are focused and compared with each other.

Many researchers have been focused various types of UAV such fixed wing [9, 10], rotary wing [11, 12]. In this study, the relative navigation methods are defined general types of UAVs, not individually. For a desired swarm concept, there are two basic sections [13], one of them is navigating the formation and the other one is maintaining the formation. As a navigating aspect, the flight path of UAVs formation is determined for the

\*: Corresponding Author Tuncay Yunus Erkeç, tuncayyunus@gmail.com, Tel: +90 531 6543003  
DOI: 10.23890/IJAST.vm01is02.0202

leader to along track [14]. On the other hand, maintaining the UAV formation is related to, detecting, estimating and controlling the relative vector states of the UAV which are included in formation [15].

Some studies in the literature, Global Navigation Satellite System (GNSS) based relative navigation methods are seemed rightly and practiced excellently navigate to UAVs. Some research shows that, aerial refueling can be autonomously made by GPS based relative methods with UAVs via Relative Time Space Positioning Information (R-TSPI). Vertical Accuracy is degraded about 1cm and Horizontal accuracy is degraded about 3cm with 10 Hz GPS receiver via Extended Kalman filter (EKF) within GPS based relative navigation [16].

The relative approaches which are focused in this study, can be used for not only UAVs platforms but also space, terrestrial and naval platforms relative state vectors estimation. Besides the errors in the GPS measurement can be eliminated via filters and estimation algorithms via fault tolerant approaches. Positioning vectors can be predicted precisely regardless of GPS errors.

The main highlights of the paper can be summarized as follows. First, to focused the Guidance, Navigation and Control (GNC) architecture of UAV's formation. Control approach requirements are denoted. Seconds, target UAV's state vector tracking, estimation and control models are explained. Collision avoidance can be executed by the relative state vector estimation and control signals during formation performed as well. Algorithms which used for relative state vector estimations of UAVs in formation are highlighted. Third, the comparisons of relative models are defined with different aspects within one hand.

## 2. Control of Formation

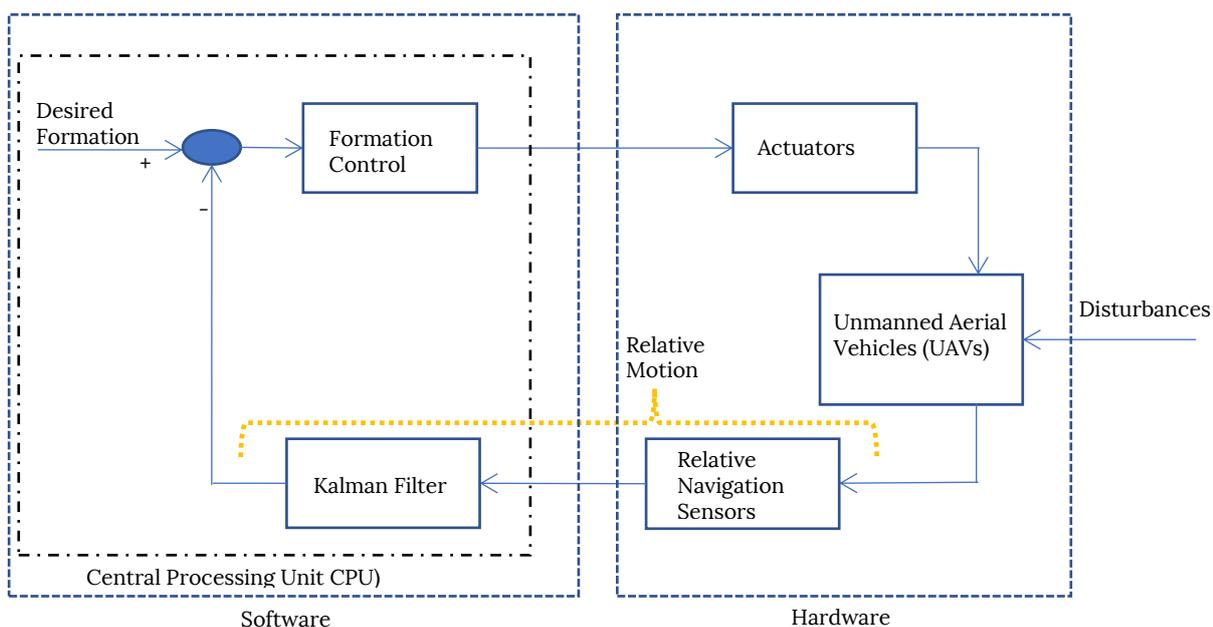
A proper and careful understanding of the user needs for formation flying of UAV is key for an adequate design, implementation and operations of mission. The user requirements are driving each of these three activities :

- Design; Relative navigation sensors, actuators,
- Implementation; Number of ground stations,
- Operations; Level of onboard autonomy.

Understanding the user needs has a massive influence on the functionality and feasibility of the mission, as well on the cost and schedule of implementation. Unfortunately, this understanding is a very difficult task for most UAV missions, as the user and engineers typically have a completely different background with very limited insight into each other's domain and using different domain languages.

In this study, a key question to be answered is that of knowledge versus control. Two approaches may illustrate this question. A sensor web which is composed of swarm UAVs, once established in flight path, typically must either not be controlled at all, or only with moderate accuracy. To evaluate the payload data, collected by the web, it is usually sufficient to determine the positions of the UAV traditional-on- ground. Thus, a posteriori knowledge of the absolute and relative positions is fully sufficient. In this case, direct inter-UAV links or actuators may not be required by the mission.

On the other hand, a virtual instrument, distributed on two UAVs flying in formation, might need a constant distance between the UAVs. In this case, traditional knowledge is insufficient. Instead, a real-time knowledge of relative position is required which is the basis for a real-time control of the relative motion of the UAVs.



**Fig. 1.** Guidance, Control and Navigation (GNC) architecture for formation flying UAVs .

In such as case, a direct inter-UAVs link for cross-communication might be necessary along with precise relative navigation sensors and actuators. Guidance, Navigation and Control (GNC) (Fig.1), is vital sub-architecture for relative navigation of UAV missions [17].

As a result, there is no generally valid approach to establish the needs for controlling a formation. Knowledge versus control, availability versus control, availability versus latency, onboard autonomy versus ground automation, sensitivity versus robustness, are key trades to be performed when designing a formation flying mission.

### 3. Guidance Navigation and Control Concepts of UAV Formation

Establishing a formation of UAVs in flight path requires two phases: the acquisition of the formation and its maintenance, termed station-keeping. The acquisition phase depends, among others, on the concept of operations which describes e.g. how many platforms are applied to flight paths. Once formation is acquired, differential accelerations will slowly but gradually destroy the initial configuration. Depending on the specific users' needs for the mission, an active control of the relative geometry of the formation might thus be necessary.

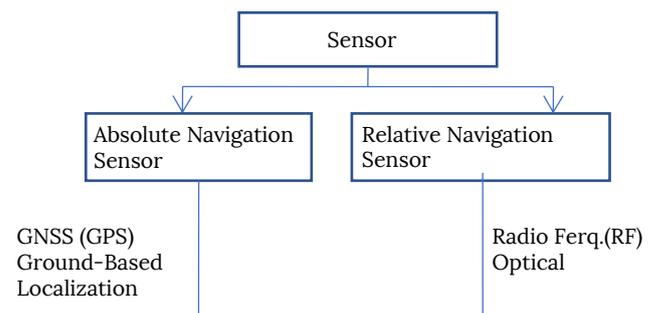
Guidance, Navigation and Control (GNC) system must be installed which enables the platform-keeping of the formation during the desired time frame. Typically, a closed-loop control scheme is implemented onboard the UAVs (Fig.1). Guidance information for the formation may originate from ground operations or an autonomous process onboard the UAV. A formation control function determines actuator commands which trigger the activation of actuators. A potential misalignment of actuators and their non-ideal performance as well as external disturbances cause a deviation in the imposed velocity increment which, over time, originates in a slightly non-nominal relative position. The navigation sensors may not be able to sense the complete 6-dimensional state vectors. Thus a subsequent relative flight path determination function is necessary. As a consequence, the measured relative position will be different from the determined relative position.

Relative navigation relates with optimal state estimates about the position and velocity of one platform relative to the other one [18]. There are many traditional applications either as GNSS&INS integrated or ground based applications. However, these applications require extra link between components and sensor fusions sections [19]. Aside from these applications, the novel ones employ optics and image processing and detection & tracking models which are in line with enhancing image process and computational technologies. The aim of novel relative navigations models is to avoid from the complexity and increase the accuracy.

### 3.1. Sensors, Actuators, Software

Sensors for relative navigation and actuators for formation control are, together with a potential direct inter-UAV link, the key hardware components for formation flight (FF). In addition, operations of FF mission typically require excessive software, both onboard as well as on-ground. The requirements for all those key elements are driven by the specific user needs for the mission.

Here, one might either select existing absolute navigation sensors which might be used to differentiate the sensor data from several sensors (Fig.2) prior to or within flight path determination function to derive the relative flight path of FF UAVs. GPS receivers or conventional ground based tracking can be used for this purpose. Alternatively, dedicated FF navigation sensors may be used which are either based on radio-frequency (RF) measurements [20] or optical measurements [21]. Dedicated sensors are typically the most expensive option. However, especially RF sensors may be used in addition to distance sensing for inter-UAV communications which renders their use attractive for high-demand FF missions.



**Fig. 2.** Guidance, Control and Navigation (GNC) architecture for formation flying UAVs.

If a FF mission requires a dedicated acquisition phase and station keeping phase that needs to be controlled, actuators, which can actively change the relative motion of the formation, are typically required. Actuators may not only be used for formation acquisition and station-keeping, but may equally well be used for reconfiguration or resizing of the formation in the course of the mission. In addition, actuators may be used as well for a station-keeping of the absolute flight path of the formation. Actuators are most commonly thrusters and rotors which provide acceleration in a continuous or non-continuous mode. In selecting adequate thrusters for FF missions, key performance parameters are thrust level, or maximum duration of thrust. Design trades have to consider among others a potential distribution of maneuver capabilities over several UAVs in the formation and risk mitigation strategies for possible failure modes.

*GNSS&INS Integration Based Relative Navigation Method of UAVs*

Theoretical approaches are used for understanding of general relative navigation technology. Relative extended Kalman filter is used for integrating and upgrading heading and distance data acquired from GPS and Internal Navigation Systems (INS). This method calls for an additional link between the relative UAVs considering the transport navigation, speed, and attitude information. The GNSS&INS integration mathematical model has been shown Eq. (1-14).

GPS based relative navigation of UAVs with Relative Time Space Positioning Information (R-TSPI) accuracy is degraded to  $\pm 1.0$  m Position,  $\pm 0.1$  m/s velocity,  $\pm 0.50$  [16].

$$\Delta X_{ps}^p = X_p^p - X_s^p \quad (1)$$

$X_p^p$  Primary's coordinates in primary plane,

$X_s^p$  Secondary's coordinates in primary plane,

$\Delta X_{ps}^p$  Location difference between primary and secondary, these vectors can also be obtained from the primary/secondary strapdown inertial navigation solutions after transferring to the reference (eccentric) point. These vectors are transformed to the inertial frame, i-frame for using Eq.(1);

$$\Delta X_{ps}^p = R_i^p (X_p^i - X_s^i) \quad (2)$$

$R_i^p$  Transformation matrix of i-frame to p-frame, where is the Primary attitude matrix which transforms from the i-frame to the p-frame. Eq. (2) represents the fundamental equation, from which the relative navigation equations are derived. This process is started by defining an interface frame, called a-frame, which is a completely arbitrary frame that rotates with respect to the i-frame. It should be noted that in this application everything is represented in the body frame of the primary, i.e., a=p. The relative position in the a-frame has coordinates in the i-frame given by:

$$(X_p^i - X_s^i) = R_a^i (X_p^a - X_s^a) \quad (3)$$

Taking one time derivative of Eq. (3) yields the relative velocity dynamic model;

$$(X_p^i - X_s^i) = R_a^i X_{ps}^a \quad (4)$$

a-lane is determined arbitrary as interface. It can change

for i-frame. While solving navigation problem; All coordinates should be based on converted to primary object coordinate system.

$$\Delta \dot{X}_{ps}^i = R_a^i \Delta \dot{X}_{ps}^a + R_a^i \overrightarrow{\Delta \dot{X}_{ps}^a} \quad (5)$$

In Eq. (5), the time derivative of the rotation matrix can be written via Eq.(6);

$$\dot{R}_a^i = R_a^i \Omega_{ia}^a \quad (6)$$

Where,  $\Omega_{ia}^a$  denotes a skew-symmetric matrix, elements from  $\omega_{ia}^a, \Omega_{ia}^a = [\omega_{ia}^a X]$ . Thus, Eq. (5) can be expressed as;

$$\Delta \dot{X}_{ps}^i = R_a^i \Omega_{ia}^a \Delta \overrightarrow{X}_{ps}^a + R_a^i \overrightarrow{\Delta \dot{X}_{ps}^a} \quad (7)$$

Taking the second time derivative of Eq. (7) to obtain acceleration dynamic model, the relative acceleration equation in the a-frame is established as:

$$\Delta \ddot{X}_{ps}^a = R_i^a \Delta \ddot{X}_{ps}^i - 2\Omega_{ia}^a \Delta \overrightarrow{X}_{ps}^a - (\Omega_{ia}^a + \Omega_{ia}^a \Omega_{ia}^a) \Delta \overrightarrow{X}_{ps}^a \quad (8)$$

In Eq. (8), the forcing term,  $\Delta \ddot{X}_{ps}^i$ , can be expressed by the Primary/Secondary accelerations sensed by their accelerometers,  $\overrightarrow{a}_p^p, \overrightarrow{a}_s^s$ , as;

$$\Delta \ddot{X}_{ps}^i = \overrightarrow{X}_p^i - \overrightarrow{X}_s^i = \overrightarrow{a}_s^i + \overrightarrow{g}_s^i - (\overrightarrow{a}_p^i + \overrightarrow{g}_p^i) \quad (9)$$

where,  $\overrightarrow{a}_p^p, \overrightarrow{a}_s^s$  are the specific forces, being also the quantity that is sensed by the Primary/Secondary accelerometers, respectively; and  $\overrightarrow{g}_p^i(\overrightarrow{X}_p^i), \overrightarrow{g}_s^i(\overrightarrow{X}_s^i)$  are the accelerations due to the gravitational fields in the i-frame and it is a function of the position vector for the Primary and Secondary, respectively. Using Eq. (9), Eq. (8) is given by:

Eq. (10) represents that the relative navigation equation in the p-frame can be converted to a-frame. Because, integrations should be converted into a stable coordinate system. Desirable velocity is in e-frame which is parallel with p-frame and shown as,  $\overrightarrow{V}_{ps}^p$

$$\Delta \ddot{X}_{ps}^a = R_p^a \overrightarrow{a}_p^p - R_s^a \overrightarrow{a}_s^s + R_s^a (\overrightarrow{g}_p^e - \overrightarrow{g}_s^e) - 2\Omega_{ia}^a \Delta \overrightarrow{X}_{ps}^a - (\Omega_{ia}^a + \Omega_{ia}^a \Omega_{ia}^a) \Delta \overrightarrow{X}_{ps}^a \quad (10)$$

$$\vec{V}_{PS}^p = R_e^p \Delta \dot{X}_{PS}^e \quad (11)$$

Measurement:

The time-derivative of Eq. (11):

$$\vec{Y}(t_k) = [(\Delta X_{PS}^p)_{GPS} - (\Delta \vec{X})_{INS}] \quad (14)$$

$$\frac{d}{dt} \vec{V}_{PS}^p = \dot{R}_r^p \Delta \dot{X}_{PS}^e + R_e^p \Delta \ddot{X}_{PS}^e \quad (12)$$

It is important that the distance between GPS receiver and IMU must be taken into account for calculation.

$\Delta \dot{X}_{PS}^e$  can be obtained from Eq. (9) by specialized  $a \cong e$

The GPS flight path prediction function (Fig.3) evaluates the flight path, provided by the position determination function, at 1 Hz rate and accounts for flight path maneuvers which might have been executed by the MAIN UAV in the past 30 seconds. It also outputs MAIN and TARGET UAV flight path states which are used by other onboard GNC functions as well as by the autonomous formation control function implementing the specific guidance and control algorithms described in the next sections.

$$\Delta \ddot{X}_{PS}^e = R_p^e \ddot{a}_p^e - R_s^e \ddot{a}_s^e + \ddot{g}_p^e - \ddot{g}_s^e - 2\Omega_{ie}^e \Delta \dot{X}_{PS}^e - \Omega_{ie}^e \Omega_{ie}^e \Delta X_{PS}^e \quad (13)$$

By substituting Eq. (11) and Eq. (13) into Eq. (12), it yields the desire form of the relative navigation equation in the p-frame navigation equations.

Formation UAV concept has been successfully realized with GPS / INS integration. Besides, relative states sensitivity between UAVs depend on GPS signal continuity and strength. Signal interruption due to environmental factors can cause errors in GPS / INS relative navigation solutions. Low power condition in received GPS signals may cause interference to dominate the incoming GPS signal. Especially in cluster UAV applications in urban and mountainous areas, negative situations such as GPS signal failure can be encountered. In the literature, some studies and methods have been developed to solve the fault tolerant GPS-based formation flight problem in order to protect the formation architecture and avoid collision during GPS signal interruptions [57].

Reference station is not stable, so that it can be called moving platform and it is main moving problem.

EBE (Epoch by Epoch) differential model; Vertical Accuracy is degraded about 1cm and Horizontal accuracy is degraded about 3 cm with 10 Hz GPS receiver via EKF. Real time relative pose estimations are recorded in primary UAV systems and second UAV is configured as a moving reference station [16].

Previous position information of UAV is subtracted from present position. Average values are least than 5 cm. However, link between UAVs is vital for maintaining the relative navigation. If the link or the GNSS information are exhausted, system faults will increase suddenly.

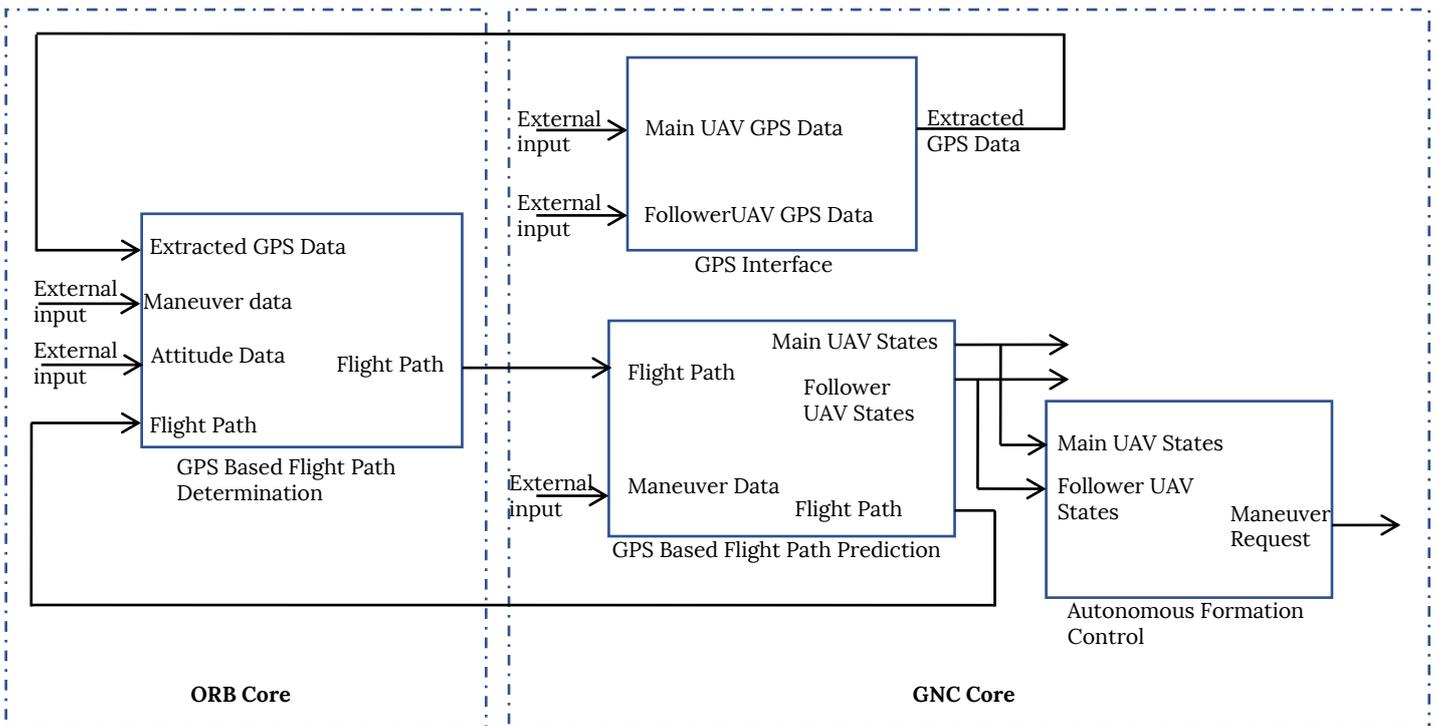
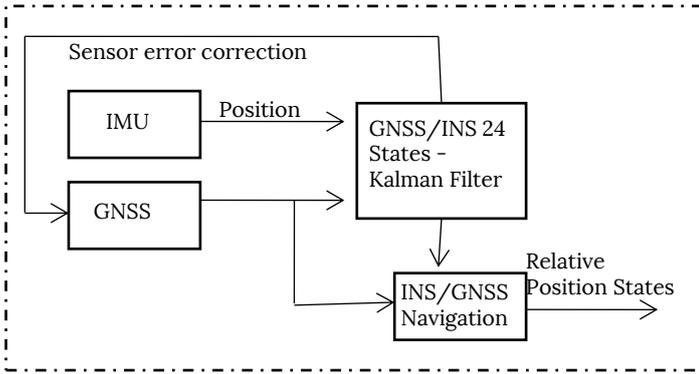


Fig. 3. Schematic software architecture for GPS based autonomous formation flying [22].

Using GPS signals, the best estimation of the relative state vectors between UAVs and minimization of errors with the 24-state Kalman filter is obtained (Figure 4).



**Fig.4.** Integrated GNSS&INS relative navigation scheme of UAV formation [24].

*INS and Vision Integration Based Relative Navigation Method of UAVs*

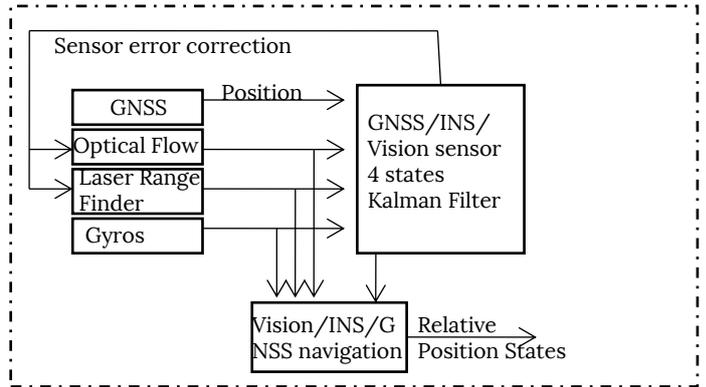
Vision based sensors and INS fusion techniques, which are used for relative navigation, have been awakened some researchers interest since the developing technology via letting both INS and vision-based sensors getting smaller, lighter and cheaper. In some of these techniques, measurements are processed consecutive sequence rather than stack. Therefore, it is neither requires storing the full data set nor re-processing the existing states data when a new measurement becomes available [25].

Once single and noisy camera is used within INS&VISION based integration, INS itself can predict and detect position, orientation and velocity parameters via Inertial Measurement Unit (IMU). Through this prediction, sheer update of INS parameters (position, velocity and attitude) stands for the primary objective [26].

Owing to multi-sensor integration, relative UAV navigation is increasingly used in cluster UAV applications to achieve low cost and precise solutions. In recent years, more accuracy and precise solutions have been obtained thanks to the integration of visual based navigation sensors and GPS / INS based sensors. Movements and state vectors of other UAVs in the formation can be relatively detected with the CCD camera [27]. Stereo image processing is applied to determine the positions relative to each other within the UAV flight path navigation and formation, and the position information obtained from this processed image provides extra navigation information to GPS / INS based relative UAV navigation [28].

In the literature, studies on UAV formation architecture are increasing day by day with the use of GPS / INS / Visual based sensors together. High resolution CCD camera and complementary Laser Range Finder (LRF)

can be used to make precise estimates of state vectors in 3 axes by detecting relative motion between UAVs (Figure 5).

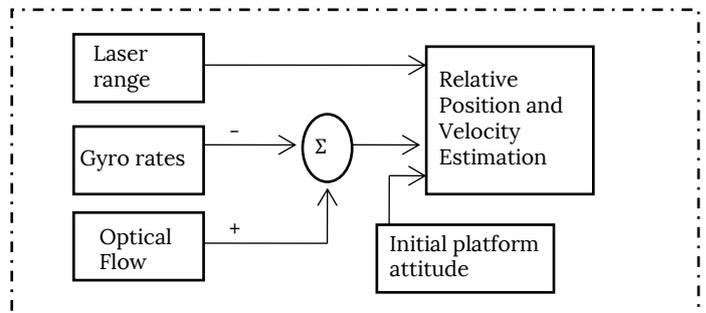


**Fig.5.** Integrated GNSS/INS/Vision based relative navigation scheme of UAV formation [24].

*Vision Based Relative Navigation Method of UAVs*

By and large, visual based navigation systems are applied so as to mitigate the dependency of external systems like GNSS during relative navigation missions [29].

The Vision Based Relative Navigation systems have been designed for near vicinity movements in UAV concept as rendezvous, docking and formation maneuvers. . Known position of the target in close range is specified by 2D, 3D or stereo imaging sensors (Fig.6). Relative position vector estimations and optimization of UAV, collision observations are calculated simultaneously. Calculated positions states are used for control systems which designated executing necessary corrections as if  $\Delta V$  avoiding and corrective maneuvers within docking, formation flight, collision avoidance system [30]. However, Vision-based navigation has also been focused highly [31,32]. Terrain Aided Navigation System (TANS) typically useable of internal sensors and terrain database which prepared in advance [33,34].



**Fig.6.** Vision based relative navigation flow chart [24].

Camera (Optic) has two direction errors. Vision based navigation state estimations are determined with LRF due to third direction respectively and denoted as LOF.

Hence, EKF is composed for estimating these errors with 4 states as shown as Eq. (15) [24].

$$X_{LOF} = [\delta\eta_b, \delta\eta_f, \delta\omega_{fx}, \delta\omega_{fy}] \quad (15)$$

Where,  $\delta\eta_b$  and  $\delta\eta_f$  denote the LRF constant bias and measurement error.  $\delta\omega_{fx}$  and  $\delta\omega_{fy}$  camera (optic) flow measurement error x and y axis respectively.

The dynamic model of these four error states are used as zero mean Gaussian white noise.

The measurement vector z is determined by Eq. (16);

$$Z_{LOF}(t) = [V_{LOF}^H - V_{GPS}^H]^T = [H_{2 \times 4}]X_{LOF}(t) + V_{2 \times 1}(t) \quad (16)$$

Where,  $V_{LOF}^H$  and  $V_{GPS}^H$  are visual and GPS velocity measurements respectively.

UAV horizontal velocity in the body frame can be determined from the camera (optic), LRF and gyro angular rate have been determined by Eq. (17).

$$V_{bxy} = (\Omega_{xy} - \varphi_{xy}) \times r_{gz} \quad (17)$$

$V_{bxy}$  are denoted translation velocities,  $\Omega_{xy}$  camera (optical) measurement of angular rate,  $\varphi_{xy}$  are denoted rotation rates at two horizontal axis,  $r_{gz}$  is denoted height measurement which comes from LRF as noted Eq.(17).

The camera (optical) and LRF navigation error model is derived via Eq. (18);

$$V_{gxy} = [\Omega_{xy}(1 - \omega_{fxy}) - \varphi_{xy}](r_{gz} - \eta_b)(1 - \eta_f) + \varepsilon \quad (18)$$

$\varepsilon$  is denoted bias due to sloping of Earth and errors EKF errors can be derived as Eq. (19);

$$\delta V_{gxy} = (r_{gz} - \eta_b)(1 - \eta_f)\delta\omega_{fxy} + [\Omega_{xy}(1 - \omega_{fxy}) - \varphi_{xy}] [(1 - \eta_f)\delta\eta_b + (r_{gz} - \eta_b)\delta\eta_f] \quad (19)$$

Hence, Eq. (20) represents the  $H_{2 \times 4}$  matrix in Eq.(16);

$$H_{2 \times 4} \begin{bmatrix} [\Omega_x(1 - \omega_{fx}) - \varphi_x](1 - \eta_f) & [\Omega_y(1 - \omega_{fy}) - \varphi_y](1 - \eta_f) \\ [\Omega_x(1 - \omega_{fx}) - \varphi_x](r_{gz} - \eta_b) & [\Omega_y(1 - \omega_{fy}) - \varphi_y](r_{gz} - \eta_b) \\ (r_{gz} - \eta_b)(1 - \eta_f) & 0 \\ 0 & (r_{gz} - \eta_b)(1 - \eta_f) \end{bmatrix} \quad (20)$$

The stochastic model of the EKF and the parameters should be designed according to the sensors' specifications.

### *Simultaneous Localization and Mapping (SLAM) Based Relative Navigation Method of UAVs*

Simultaneous Localization And Mapping (SLAM) algorithm can be used to navigate UAVs in an unpredictable environment [35]. Since the onboard vision sensors detect landmarks on the other platforms

and environment for relative navigation of UAVs. The SLAM estimates the platform position vectors with successive edge detection and observations [36,32].

Odometers, radar, GPS and several types of range finders such as sonar, laser and infrared supported sensors are commonly employed in SLAM techniques [37, 38]. BOSLAM (term Monocular SLAM is also used) as a fine solution to the SLAM problem is so helpful for supplying relative measurements. There have been a series of tremendous enhancements for BOSLAM over last year's [39-42].

The SLAM techniques are practical for indoor and/or outdoor environments and build up enormous splash Guidance, Navigation and Control (GNC) research field. In this day and age, vehicles are able to reach out to next flight through way-point and hold their exact position by using only visual data provided by the SLAM framework for marking the target of UAV missions. Some principal topics are robustness of solutions to the loss of the properties in the video images, being late in the communication processes, ways of eliminating the slow drift in behavior could have far more importance for long flights, succession UAV's environments without any external support [26].

### *Light Amplification by Stimulated Emission of Radiation (LASER)/Light Detection and Ranging (LIDAR) Based Relative Navigation Method of UAV*

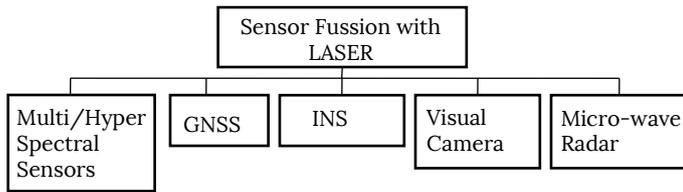
Laser systems are used for different kind of applications within Space and UAV as if Laser Range Finders (LRF) and Laser Target Designators (LTD), Laser Radars (Light Detection and Ranging-LIDAR), Laser Communication Systems (LCS) and Directed Energy Weapons (DEW). Besides, relative navigation, docking, 3D stereo mapping, remote sensing, detection, collision warning and obstacle avoidance are used with Laser/Lidar sensors frequently [43, 24].

Laser/Lidar based systems are used for different functions with different measurement techniques (Table 1).

Laser/Lidar systems can be used individually besides they are integrated into other systems (Fig.7) via sensor fusion due to increasing accuracy of relative state estimations and they are back up for laser sensors limitations due to atmosphere affects as if fog and clouds.

**Table 1.** Laser systems Functions and Measurement Techniques [44]

Functions	Measurements
Tracking, Sensing, Imaging	Amplitude (Reflectance)
Moving Target Indication (MTI)	Range (Delay)
Machine Vision	Velocity (Doppler Shift or Differential Range)
Velocimetry	Angular Position
Target Detection, Identification	Vibration Level



**Fig. 7.** Sensor Integration of UAVs formation concept [44].

Most laser systems are active devices that operate in a similar way to electromagnetic waves radars but at much higher frequencies (Table 2) [19].

**Table 2.** Wavelengths of some laser types [44].

Types of Laser	Wavelength
CO2	9.2-11.2 μm
Er:YAG	2 μm
Nd:YAG	1.06 μm
GaAlAs	0.8-0.904 μm
HeHe	0.63 μm
Frequency DoubledNd:YAG	0.53 μm

The useful effects of airborne laser systems including the smaller component and accurate angular resolution have been resulted in several UAV applications [24]. However, laser sensors are so vulnerable to dust, fog, and cloud of the atmosphere that makes these sensors far more limited within close ranges than microwave systems. Hence, analyzing the performance of laser sensors and systems in various weather and environmental conditions are substantial. What is more, specified airborne laser safety is considered as an important criterion due to the fact that multiple systems currently used within the near infrared create an enormous risk for the naked human eye. At this view, laser-based technologies are not considered as green methods, yet these technologies can use several platforms thanks to the locating accurate position and angular measurement abilities. Nonetheless, power consumption and weight always becomes a challenging issue for UAVs, therefore cost-effective Laser/Lidar

sensors have been tried to be invented over last decades [44].

The microwave radar range equation is applied to laser systems and the power received by the detector  $P_R$  is given by Eq. (21);

$$P_R = \frac{P_T G_T}{4\pi R^2} \frac{\sigma}{4\pi R^2} \frac{\pi D^2}{4} \tau_{atm} \tau_{sys} \quad (21)$$

Where,  $P_T$  is the transmitter power,  $G_T$  is the transmitter antenna gain,  $R$  is the range (m),  $D$  is the aperture diameter (m),  $\tau_{atm}$  is the atmospheric transmittance and  $\tau_{sys}$  is the system transmission factor. With laser systems, the transmitter antenna gain is substituted by the aperture gain, expressed by the ratio of the steradian solid angle of the transmitter beam width  $\alpha^2$  to that of the solid angle of a sphere which is noted Eq. (22).

$$G_T = \frac{4\pi}{\alpha^2} \quad (22)$$

*Relative Navigation Algorithms for UAVs*

In this part, as mentioned above, using algorithms for control section of UAVs which are used for not only sensor fusion but also detect and estimate the target UAV motions, UAV's movements such as Kalman, particle filters. Estimation of States, which are converted from non-linear movement characterize to linear within a divided time periods are predicted. On the other hand, math and physical models of system must be well defined.

For linear randomize systems, Kalman filters are well-known for their popular state estimation, prediction, optimization techniques [45]. One interesting issue as to Kalman filters is that they call for an precise system model and accurate noise statistics data. By virtue of these restrictions, applications can be hardly implemented in real life. Deficiency of information causes enormous estimation errors as well as filter accuracy.

Some of related works on monocular SLAM predicated on extra sensors [46], Extended Kalman Filter (EKF) is improved for velocity position and behavior estimation of a UAV with using low-cost sensors which are created by a sensor-fusion algorithm. Especially, an IMU and an optical-flow sensors which include a laser module and an extra gyroscope can be used [29]. In fusing inertial sensors with camera in an iterated EKF is suggested.

The extended Kalman filter (EKF) has been the most comprehensively used application for nonlinear filtering problems so far. However, it works well only in the linear regime in which the linear approximation of the nonlinear dynamic system and it is compatible only when the observation model is valid [47]. Recently, a

cubature Kalman filter (CKF) [48] based on the third-degree spherical-radial cubature rule has been proposed and employed with various applications, such as positioning [49], sensor data fusion [50] and attitude estimation [51]. The cubature rule is derivative-free and the number of the scaled cubature points is linearly with the state-vector dimension, which makes the CKF could be applied in high-dimensional nonlinear filtering problems. Compared with the EKF, the CKF has better convergence characteristics and greater accuracy for nonlinear systems [48]. According to the academic simulation outcomes, the proposed filter provides far more accurate estimates for relative attitude and position than the extended Kalman filter [47].

Some researchers also use different algorithm systems which are Monte Carlo Simulation Method [52, 53], Lyapunov Method [54, 18], etc. or novel versions of Kalman filters as if Cubature Kalman filters [47], Adaptive Fading Kalman Filters (AFKF) [55, 56], Federal Kalman Filters, for increasing accuracy of linearization, estimation, optimization of states within not only flying vehicles but also all movement vehicles for autonomous control, docking, relative navigation aims [57]. Multiple hypotheses filters, filtering techniques, Sum of Gaussians [58], Particle Filters [59] and extensively various estimation and filtering techniques [60] have been studied by some authors.

Some of the most eligible notes of these works still are based on the well-known Extended Kalman filter [61,62]. Kalman filters have proven themselves not only in theory but also in practical usage of real systems. However, state estimation of non-linear stochastic systems suffering low performance and repellency along with the noise distribution in the Unscented Kalman Filter (UKF) are incompatible to a real system which is broadly used by UKF [63].

### 3.2. Impact on Mission Architecture and UAV Bus

Designing, implementing and operating a successful FF mission needs to consider the FF mission needs to consider the FF aspects on all elements of the mission architecture.

1. Subject,
2. Flight path and constellation, (design of relative formation geometry)
3. Payload, (Camera, military payload)
4. Platform, (UAV body types)
5. Ground element,
6. Mission operations,
7. Command, Control and Communications architecture (inter-UAV link, relay options)

From an engineering point-of-view, the impact of FF on the UAV, payload and bus are most interesting. Of these two aspects, the payload is critically driven by the user

needs. For the UAV bus, FF does not only affect the navigation sensors and control actuators as described above, but has an impact on various other subsystems.

- Attitude Control System (ACS) (relative pointing for payload operations or inter-UAV link),
- Guidance, Navigation, Control (GNC)(additional relative GNC functions),
- Propulsion (Prop) (FF control and flight path control),
- Structures and mechanisms,
- Electrical Power System (EPS),
- Thermal Control Systems (TCS),
- On board Data Handling System (OBDH),
- Telemetry, Tracking and Command (TTC) (additional bandwidth for payload and FF operations)

## 4. Results and Discussion

For autonomous UAV systems, complexity reveals itself in different ways;

1. Complexity of environment,
2. Complexity of task to be perform,
3. Complexity of Co-operation between multiple autonomous systems.

The environment encountered by autonomous system varies in a large scale. Generally, UAVs operate in relatively simple and forgiving environments. On the contrary to the ground plane, a UAV's environments are utterly obstacle free. Although a world representation is not required for UAV's environment, there are slight environmental conditions which create other forms of complexity. This complexity can be separated into two groups;

Firstly, atmospheric effects such as turbulence, shear and vortices influence the vehicle's motion dramatically. These effects may have a considerable influence on the vehicles linear and angular motion, and they are potentially catastrophic in terms of accident.

Secondly, other contributors are to accounted as complexity of boom motion during aerial refueling, deck and optical system motions during carrier landing.

Ascribed to the complexity associated with environments, autonomous vehicles have to sense to a certain degree in order to comprehend their environment. The process of representing and understanding the Earth can be deemed from many aspects. For instance, a stationary sensor has the ability to create an Earth representation, yet its inability to move regards that representation has a constricted internal use. A sensor located on a man plotted vehicle can create an Earth representation since the humans are

able to enhance situational awareness by interpreting and understanding the Earth. Tele-operated vehicles call for a human guidance in the loop in which there is a heavy dependence upon human for input and guidance. Therefore, the tele-operated vehicle has limited requirements for Earth representations [64].

Complexity, automation and autonomy appear as a whole single entity as well as multiple platforms. In this regard, each system may be preferable depending on the mission requirements. A problem expected to well resolved by single asset solution could be identified. Below there is a bunch of characteristics which shown in Table 3 as an example to this identification.

**Table 3.** Comparison of single and multiple UAV concepts [64].

Single Platform	Multiple Platforms
Hard to separate into pieces, Highly interdependent system dynamics,	Easy to separate into pieces., Dynamics are loosely coupled, Time-scale separation is apparent,
Physical dispersion adds little benefit, Simultaneous actions add little, Sequential tasking is adequate/optimal,	Physical dispersion can be used to great effect, Simultaneous tasking has great utility, Sequential tasking is inadequate,
Information transfer is costly/inadequate, Threats make communication undesirable, Geographic separation makes communication difficult, Terrain/environment make communication difficult.	Information transfer is not costly, A global information state can be maintained, Local information is adequate, Lags and latency are acceptance.

All these with the caveat of the complexity problems are so overwhelming that separation remains the sole realistic option available. The benefits of having multiple assets add degrees of freedom to the problem resolution. However, this flexibility comes with a cost which could be regarded as an additional complexity imposed in the form of limitations. A target must be validated before an attack and battle damage has to be assessed before the attack. For this reason, the meaning of “complexity and automation” for multi-platform systems probably imply different concepts from those associated with single platform systems.

Other key factors that make a multi-asset solution aside from a single-asset solution are:

1. Problem division,
2. Information availability.

The former includes actions/items such as order of precedence (kill chain), coupling of tasks, performance and computations. The latter deals primarily with communication, centralization of processing,

correlation of targets and moving platforms [55].

In the formation architecture, the joint movement between UAVs and the behavior characteristics of a single UAV are preserved during the decision process. The architecture was established on a single center control. Meanwhile, there must be a communication between all UAVs via the inter-UAV link. Task features, cross-platform communication, and uncertainty management have an impact on the interoperability level. This situation creates a complex structure. There is no collaboration process that can take all inputs and variables into account. However, by dividing it into sections, the solution is tried to be simpler, although the totality is lost. Although this solution is not the best solution for collaboration and task, it is a solid and acceptable solution.

Cluster UAV control and optimal selection problem can be separated functionally by numerical and mathematical models. In the UAV formation concept, subset and task formation can be done in conjunction with theoretical methods [65], discretization approaches [66] and relative profit-loss techniques [67]. Subset optimization problem can be examined under many subtitles. While determining and simplifying the main mission goal, the task and timing of each platform forming the formation should be determined. Each UAV sends its mission requirements and information to the central decision department. Algorithms for multitasking, heuristic search methods, discretization and limiting [68], linear programming approach [68] include iterative network flow. The complexities of multitasking can be absorbed by task integration.

#### 4.1. Comparison

Traditional techniques such as GNSS, INS based on integration are used in UAV's as well as other platforms. Also, these techniques are both compatible with commercial planes, cars, ships and not energy limited opposes to small UAVs. However, a lot of studies are focused on techniques for these platforms not only fixed wing but also rotary wing [69,70] due to autonomous control, especially Guidance, Navigation and Control (GNC).

Traditional methods like GNSS based relative navigation approaches have been limited by coverage area which served by GPS, GLONASS, GALILEO satellites, on the other hand, it gives more accurate and continuous location information and also cost effective for designing small UAV's power systems. Using GNSS and ground stations for relative navigation applications are expensive. It seems like a challenge for using laser sensors within UAVs due to limited power budget. However, it can be integrated other methods like INS, laser, vision sensors.

Laser/Lidar based sensors are vulnerable to dust, fog and clouds according to wavelengths. Yet, these sensors are very accurate for detecting. Visual and GNSS based

UAVs relative navigation methods comparison is shown in Table 4.

**Table 4.** Comparison of Visual and GNSS based relative navigation of UAVs [19].

	Visual	GNSS
1.	Green Method (no energy dissipation required).	It is based on electromagnetic wave energy.
2.	Wide sensor requirements viewing range.	UAV and GNSS coverage is required.
3.	Short distance solutions.	Relatively long-distance solutions.
4.	The extra inter-UAVs link is not required, provided autonomous solutions.	Link between UAVs is required.
5.	The relative motion sensitivity depends on the sensor sensitivity.	The relative motion depends on the GNSS information sensitivity.

The sensor integration is used for overcoming these complexity and navigation issues in formation concepts. The sensors vary according to accuracy and data rate which used for measurement from source. The sensor properties are shown in Table 5. Kalman filters are used for integrating sensor. Inter-UAV link should be established for sharing navigation data in formation.

**Table 5.** Example of sensor properties for UAV navigation [24].

Sensors	Data Rate	Accuracy
INS (IMU7000CB)	50 Hz	Gyro: Scale <2% Bias<20deg/hr Accelerometer: Scale<1%
GPS (Novatel RTK)	20 Hz	2 cm 0.05m/s
Optical (CCD Camera)	50 Hz	Scale<2%
LRF	25Hz	Scale error<1% Offset<10cm

## 5. Conclusion

In this Study, relative navigation methods which are used for UAVs are focused on different approaches. The vision based relative navigation methods have been attracted attention by some researchers during last decades thanks to their remarkable advantages. However, traditional GNSS and INS based methods have proven themselves at online platforms within several environments even though they have coverage limitations.

Algorithm types which used for estimate states of relative parameters are chosen according to analyzing the nonlinear motion. Kalman filters such as extended, unscented, cubature algorithm models need input data which come from measurement and models. However, they are run by online system simulations successfully.

Formation flight concept on UAVs is focused in this study and compared between single and multiple platforms usage for UAV in the area of interest. Besides, Vision based and GNSS based relative states estimation approaches are compared each other.

The methods of UAVs are relative navigation state estimates are chosen according to platform, mission and accuracy requirements. The sensor and algorithms development will be affected to selecting relative approaches on UAVs. The final point of relative method selections is fully independent, autonomous and effective due to mission requirements.

In conclusion, the article highlights the relative navigation methods of UAVs and the impact factor of formation architecture from different perspectives. The complexity and comparison between relative methods are examined in terms of motion detection sensor properties. With this study, it is aimed to be a guide in the selection of relative navigation methods and predictions of their complexities in future formation unmanned aerial vehicles missions, taking into account the environment, mission and platform characteristics.

## Abbreviations

UAVs	:	Unmanned Aerial Vehicles
GNSS	:	Global Navigation Satellite System
INS	:	Inertial Navigation Systems
EKF	:	Extended Kalman Filter
GPS	:	Global Positioning System
SLAM	:	Simultaneous Localization and Mapping
R-TSPI	:	Relative Time Space Positioning Information
EKF	:	Extented Kalman Filter
GNC	:	Guidance, Navigation and Control
FF	:	Formation Flight
RF	:	Radio Frequency
EBE	:	Epoch by Epoch
IMU	:	Inertial Measurement Unit
LRF	:	Laser Range Finder
LTD	:	Laser Target Designators
LIDAR	:	Light Detection and Ranging
MTI	:	Moving Target Indication
CFK	:	Cubature Kalman Filter
AFKF	:	Adaptive Fading Kalman Filter
ACS	:	Attitude Control System
EPS	:	Electrical Power System
TCS	:	Thermal Control System
OBDH	:	On Board Data Handling System
TTC	:	Telemetry, Tracking and Command
TANS	:	Terrain Aided Navigation System

## CRedit Author Statement

**Tuncay Yunus Erkeç:** Writing-Original draft preparation, Writing-Reviewing and Editing, Software, Investigation, Data Curation. **Chingiz Hajiyev:** Supervision, Conceptualization, Validation, Project administration, Resources, Funding acquisition

## References

- [1] Costa F.G., Ueyama J. Braun T. Pessin G. Osório F.S. Vargas P.A. (2012) The use of unmanned aerial vehicles and wireless sensor network in agricultural applications, in Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International, 5045-5048.
- [2] Dongwoo, L., Seungkeun, K., Jinyoung, S. (2018). Formation flight of unmanned aerial vehicles using track guidance. *Aerospace Science and Technology*. 76. 10.1016/j.ast.2018.01.026.
- [3] Hausamann D., Zirnig W., Schreier G., Strobl P. (2005) Monitoring of gas pipelines—a civil UAV application, *Aircraft Eng. and Aerospace Tech.* 77 (5), 352-360.
- [4] Katrasnik J., Pernus F., Likar B. (2010) A survey of mobile robots for distribution power line inspection, *IEEE Transactions on Power Delivery*, 25(1), 485-493.
- [5] Palunko I., Cruz P., Fierro R. (2012) Agile load transportation: Safe and efficient load manipulation with aerial robots, *Robotics & Automation Magazine, IEEE*, 19(3), 69-79.
- [6] Hajase M., Noura H, Drak A., (2015) Formation Flight of Small Scale Unmanned Aerial Vehicles: A Review, In book: *Control Theory: Perspectives, Applications and Developments*, Chapter: Formation Flight of Small Scale Unmanned Aerial Vehicles: A Review, Nova Science Publishers.
- [7] Ma, O., Abad, A.F., Boge, T. (2012). Use of industrial robots for hardware-in-the-loop simulation of satellite rendezvous and docking, *Acta Astronautica*, 81, 335-347.
- [8] Rafail F.M., Budylov S.G. (2010). Short rendezvous missions for advanced Russian human spacecraft, *Acta Astronautica*, 67, 900-909.
- [9] Beard RW., McLain T.W., Nelson D.B., Kingston D., Johanson D. (2006) Decentralized cooperative aerial surveillance using fixed-wing miniature UAVs. *Proceedings of the IEEE*, 94(7), 1306-1324.
- [10] Warsi F., Hazry D., Ahmed SF. Joyo M.K., Tanveer M.H., Kamarudin H., Razlan Z.M. (2014) Yaw, Pitch and Roll controller design for fixed-wing UAV under uncertainty perturbed condition, in 2014 IEEE 10th International Colloquium on Signal Processing & its Applications (CSPA), 151-156.
- [11] Lee H., Kim S., Lim H. Kim H.J., Lee D. (2013) Control of an octa-copter from modeling to experiments, in *Robotics (ISR)*, 2013 44th International Symposium on, 1-5.
- [12] Van de Loo J. (2007) Formation flight of two autonomous blimps, PhD diss., Technische Universiteit Eindhoven.
- [13] Anderson. B, Fidan B. Yu C., Walle D. (2008) UAV formation control: theory and application, in *Recent advances in learning and control*, 15-33.
- [14] Yun B., Chen B.M., Lum K.Y., Lee T.H. (2008) A leader-follower formation flight control scheme for UAV helicopters, in *IEEE International Conference on Automation and Logistics*, 2008. ICAL 2008. 39-44.
- [15] Zhang X.T. (2006) An output feedback nonlinear decentralized controller design for multiple unmanned vehicle coordination, in *American Control Conference*, 6-9.
- [16] Moafipoor S., Bock L., Fayman J. A., Honcik D. (2014). *Fundamentals of autonomous relative navigation and its application to aerial refueling*, Geodetics Inc. San Diego, CA 92117, USA.
- [17] Gill E. (2019). *Control Approaches for Formations of Small Satellites*, NATO, Delft, Netherlands.
- [18] Alonso R., Crassidis J.L., Junkins J.L. (2010). Vision-Based Relative Navigation for Formation Flying of Spacecraft, *AIAA-2000-4439*.
- [19] Erkeç T.Y., Hajiyev, C. (2019). Traditional Methods on Relative Navigation of Small Satellites”, 2019 9th. International Recent Advances in Space Technologies Conference (RAST), Istanbul, 869-874.
- [20] Lestarquit L. et.al. (2006). Autonomous Formation Flying RF Sensor Development for Prisma Mission. *ION GNSS*.
- [21] Jorgensen J.L., Benn M. (2010). VBS-The Optical Rendezvous and Docking Sensor for Prisma, *Nordicspace*, 16-19.
- [22] Gill E., D’Amico S (2007). Autonomous Formation Flying for the PRISMA mission, *Journal of Spacecraft and Rockets* 44, 3, 671-681.
- [23] Wang S., Zhan X., Zhai Y., Chi C., Shen J. (2020) Highly reliable relative navigation for multi-UAV formation flight in urban environments, *Chinese Journal of Aeronautics*, 1-14.
- [24] Wang J., Garratt M., Lambert A., Wang J., Han S., Sinclair D. (2008). Integration of GPS/INS/vision sensors to navigate unmanned aerial vehicles. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 37.
- [25] Ristic B., Arulampalam S., Gordon N. (2004). *Beyond the Kalman Filter Particle filters for Tracking Applications*, Artech House Radar Library.
- [26] Sazdovski V., Kitanov A., Petrovic I. (2015) Implicit observation model for vision aided inertial navigation of aerial vehicles using single camera vector observations, *Aerospace Science and Technology* 40, 33-46.
- [27] Winkler S., Schulz H.W., Buschmann M., Kordes

- T., Vasman P. (2004) Improving Low-Cost GPS/MEMS-Based INS Integration for Autonomous UAV Navigation by Visual Aiding, ION GPS 2004. The Institute of Navigation, Long Beach, CA USA, pp. 1069-1075.
- [28] Tao C.V., Chapman M.A., Chaplin B.A. (2001) Automated processing of mobile mapping image sequences. *ISPRS Journal of Photogrammetry & Remote Sensing*, 55(5-6): 330-346.
- [29] Driessen S.P.H., Janssen N.H.J., Wang L., Palmer J.L., Nijmeijer H. (2018) Experimentally Validated Extended Kalman Filter for UAV State Estimation Using Low-Cost Sensors, *IFAC PapersOnLine* 51-15, 43-48.
- [30] Julian Scharnagl, Lakshminarasimhan Srinivasan, Karthik Ravandoor, Klaus Schilling. (2015), Autonomous Collision Avoidance for Rendezvous and Docking in Space Using Photonic Mixer Devices, *IFAC-PapersOnLine* 48-9, 239-244.
- [31] Jun M., Motokuni I., Shirai Y. (2002) Toward VisionBased Intelligent Navigator: Its Concept and Prototype. *IEEE Transactions on Intelligent Transportation Systems*, 3(2), 136-146.
- [32] Kim J., Sukkarieh S. (2004) SLAM aided GPS/INS Navigation in GPS Denied and Unknown Environments, The 2004 International Symposium on GNSS/GPS, Sydney, Australia.
- [33] Chatterji G.B., Menon P.K., Sridhar B. (1997) GPS/Machine Vision Navigation System for Aircraft. *IEEE Transactions on Aerospace and Electronic System*, 33(3), 1012-1024.
- [34] Ogris G., Gal C.L., Wack, R., Paletta L. (2004) Image Based Positioning in Urban Environments Using Kalman Filtering of PCA Sensors, The 4th International Symposium on Mobile Mapping Technology (MMT2004), Kunming, China.
- [35] Smith R., Cheeseman P. (1987) On the Representation of Spatial Uncertainty. *International Journal of Robotics Research*, 5(4): 56-68.
- [36] Dissanayake M.W.M.G., Newman P., Durrant-Whyte H., Clark S., Csorba, M. (2001) A solution to the simultaneous localization and map building problem. *IEEE Transactions on Robotics and Automation*, 17(3), 229-241.
- [37] Teslic L., Skrijanc I., Klancar G. (2010) Using a LRF sensor in the Kalman filtering based localization of a mobile robot. *ISA Transactions* 49, 145-53.
- [38] Vázquez-Martín R., Núñez P., Bandera A., Sandoval F. (2009). Curvature-based environment description for robot navigation using laser range sensors. *Sensors* 8:5, 894-918.
- [39] Chowdhary G., Johnson E.N., Magree D., Wu A., Shein A. (2013). GPS-denied indoor and outdoor monocular vision aided navigation and control of unmanned air-craft, *J. Field Robot.* 30(3), 415-438.
- [40] Engel J., Sturm J., Cremers D. (2012). Camera-based navigation of a low-cost quadro-copter, in: *IEEE/RJS International Conference on Intelligent Robot Systems (IROS)*, pp.2815-2821.
- [41] Engel J., Sturm J., Cremers D. (2012). Accurate figure flying with a quadcopter using onboard visual and inertial sensing, in: *IEEE/RJS International Conference on Intelligent Robot Systems (IROS)*.
- [42] Weiss S., Achtelik M., Lynen S., Chli M., Siegwart R. (2012). Real-time onboard visual-inertial state estimation and self-calibration of MAVS in unknown environments, in: *IEEE International Conference on Robotics and Automation (ICRA)*, pp.957-964.
- [43] Ramasamy S., Sabatini R., Gardi A., Liu J. (2016). LIDAR obstacle warning and avoidance system for unmanned aerial vehicle sense and avoid, *Aerospace Science and Technology* 55, 344-358.
- [44] Sabatini R., Richardson M.A., Gardi A., Ramasamy S. (2015). Airborne laser sensors and integrated systems, *Progress in Aerospace Sciences* 79, 15-63.
- [45] Auger F., Hilairet M., Guerrero J.M., Monmasson E., Orłowska-Kowalska T., Katsura S. (2013). Industrial applications of the Kalman filter: a review, *IEEE Trans. Ind. Electron.* 60(12), 5458-5471.
- [46] Strelow S., Sanjiv D. (2003). Online motion estimation from image and inertial measurements. *Workshop on Integration of Vision and Inertial Sensors INERVIS*.
- [47] Zhang L., Yang H., Lu H., Zhang S., Cai H., Qian S. (2014). Cubature Kalman Filtering for relative Spacecraft attitude and position estimation. *Acta Astronautica* 105, 254-264.
- [48] Arasaratnam I., Haykin S. (2009). Cubature Kalman filters, *IEEE Trans. Autom. Control.* 54, 1254-1269.
- [49] Personen H., Piche R. (2010). Cubature-based Kalman filters for positioning, In: *Proceedings of the 7th Workshop on Positioning Navigation and Communication*, 45-49.
- [50] Fernandez-Prades C., Vila-Valls J. (2010). Bayesian nonlinear filtering using quadrature and cubature rules applied to sensor data fusion for positioning, In: *Proceedings of the IEEE International Conference on Communications, Cape Town, South Africa*, 1-5.
- [51] Tang X., Liu Z., Zhang J. (2012). Square-root quaternion cubature Kalman filtering for spacecraft attitude estimation, *Acta Astronautica* 76, 34-94.
- [52] Melczer M., Bauer P., Bokor J., (2017). 4D Trajectory Design for Vision Only Sense and Avoid Flight Test, *IFAC Papers On Line* 50-1, 15203-15208.
- [53] Song J., Xu G. (2017). An Orbit Determination Method from Relative Position Increment

- Measurement, Aerospace Engineering SAGE, doi.org/10.1177/0954410017708803.
- [54] Felicetti L., Emami M.R. (2018). Image-based attitude maneuvers for space debris tracking, *Aerospace Science and Technology* 76, 58–71.
- [55] Xia Q., Rao M., Ying Y., Schen X. (1998). Adaptive Fading Kalman Filter with an Application, *Automatica*, 34, pp 1333–1338.
- [56] Levent O., Fazil A.A, (1998). Comments on “Adaptive Fading kalman Filters with an Application” *Automatica*, vol 34, pp 1663–1664.
- [57] Chen J., Wang X., Shaot X. and Duan D. (2010). An Integrated Relative Navigation System Using GPS/NISNAV for, Ultra-close Spacecraft Formation Flying, 3rd International Symposium on Systems and Control in Aeronautics and Astronautics.
- [58] Kwok N.M., Dissanayake G. (2004) An efficient multiple hypothesis filter for bearing only SLAM. In: *Proceedings of IEEE / RSJ International Conference on Intelligent Robots and Systems (IROS04)*, Sendai, Japan, Sep / Oct 2004, pp.736–41.
- [59] Kwok N.M., Dissanayake G. (2003) Bearing-only SLAM in indoor environments. *Australasian Conference on Robotics and Automation*.
- [60] Kwok N.M., Dissanayake G., Ha QP. (2005) Bearing only SLAM using a SPRT based Gaussian sum filter. In: *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA05)*, Barcelona, Spain, 1121–1126.
- [61] Guerra E., Munguia R., Bolea Y., Grau A. (2013) New validation algorithm for data association in SLAM, *ISA Transactions* 52, 662–671.
- [62] Simon D., (2006). *Optimal State Estimation: Kalman,  $H_{\infty}$  and Nonlinear Approaches*, Wiley, New York.
- [63] Li W., Sun S., Jia Y., Du J. (2016). Robust unscented Kalman filter with adaptation of process and measurement noise covariances, *Digital Signal Processing* 48, 93–103.
- [64] Shin H., White B. (2019). *Unmanned Aerial Vehicle Formations*, NATO, Swindon, UK, 1–28.
- [65] Binmore K. (2007) *Game Theory: A Very Short Introduction*, OUP Oxford.
- [66] Valavanis K.P., Vachtsevanos G.J. (2011) *Handbook of Unmanned Aerial Vehicles*, Springer.
- [67] Shima T., Rasmussen S. (2009) *UAV Cooperative Decision and Control: Challenges and Practical Approaches*, Society for Industrial Mathematics.
- [68] Butenko S., Murphey R., Pardalos P.M. (2010) *Cooperative Control: Models, Applications and Algorithms*, Springer.
- [69] Adamski W., Herman P. (2012) Comparison of two- and four-engine propulsion structures of airship, in *Robot Motion and Control*, 341–350.
- [70] Bestaoui Y., Hima S. (2007) Modelling and trajectory generation of lighter-than-air aerial robots-invited paper, in *Robot Motion and Control*, 3–28.