Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Deep Learning-Enhanced Sensor Fusion for Autonomous Unmanned Aerial Vehicle Navigation

Farhan Ali*
School of Computer and IT, Beaconhouse National University, P.O. Box 53700 Lahore, Pakistan Email: farhan32748@gmail.com

ABSTRACT

The proliferation of Unmanned Aerial Vehicles (UAV) in the civil and military sector has demanded the development of more potent yet precise navigation systems capable of operating under the hostile and mobile environments. The stability of the autonomous is obligatory to be the aspect of precision state estimation, path planning and obstacle avoidance. However, each sensor suffers independent failures such as drift of Inertial Measurement Unit (IMU) and signal jamming in a Global Navigation Satellite System (GNSS). In this review paper, the state-of-the-art of the two sensor fusion designs on autonomous UAVs and navigation sensors will be discussed in detail. We are critical of core sensor principles of operation and constraints like IMUs, GNSS, Vision, LiDAR, and Magnetometers. Besides, we review the available literature on the sensor fusion algorithms, both conventional types of Kalman Filters and the more recent types of Simultaneous Localization and Mapping (SLAM) and the newer Deep Learning-related approaches. According to the review, the trend has been towards edge-computing solutions and using multi-modal sensor redundancy to resolve the GNSS-denied environments. We end up by establishing important challenges and recommending the future research path of hybrid AI based fusion and collaborative swarm localization.

Keywords: Autonomous UAVs; Navigation Sensors; Sensor Fusion; INS/GNSS; Kalman Filter; SLAM.

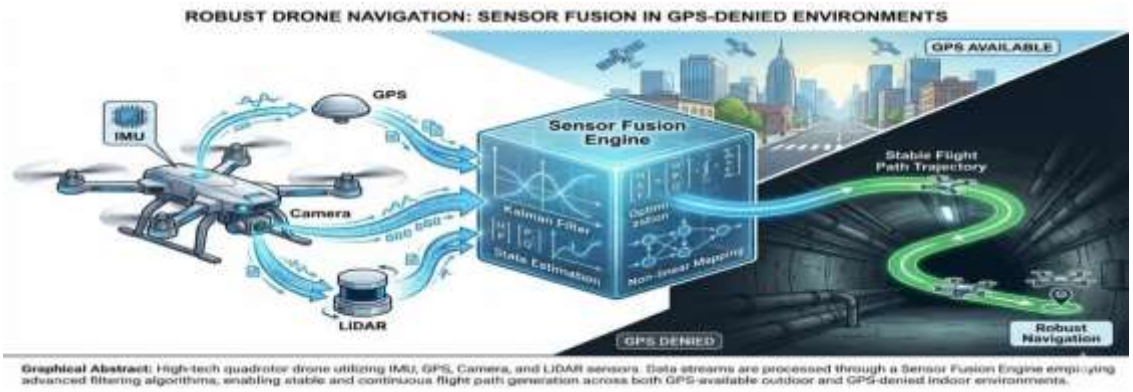


Figure 1: Show the graphical abstract

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Introduction

The Evolution and Ubiquity of UAV Systems

Drones (Drones are also known as Unmanned Aerial Vehicles or UAVs) are out of their niche in the history of the world as a military reconnaissance device, and have become an ubiquitous technology in the world of the commonplace. The democratization of Micro-Electro-Mechanical Systems (MEMS) sensors and high-performance density batteries that have been steadily ongoing in the last decade has led to an exponential rise in the uses of UAVs. The current UAVs no longer rely on a line-of-sight remote control, instead they are being incorporated as complex data-gathering nodes into the Internet of Things (IoT) system.

The space of the works of the modern UAVs is tremendous. In precision agriculture, drones equipped with multiple spectra's can be applied to check the well-being of crops and to spray pesticides automatically to optimally obtain the maximum crop harvest and reduce the consumption of chemicals [2]. In civil engineering, structural health surveys of important infrastructure, such as bridges, dams, power lines etc., can be performed using UAVs to reduce the risk of exposing human inspectors to such dangers, and increase throughput of safety inspections [3]. Besides, the other direction of the logistics industry exploration is the implementation of the so-called last-mile delivery, where the agility and speed of the vertical take-off and landing (VTOL) vehicles offer a decisive advantage over the ground transport system in congested cities [4]. However, this transition to the actual world implementation places massive strains upon the base navigation systems. This implies a paradigm shift in robotics: UAVs would no longer need to work within a programmed path; they will be supposed to detect their dynamic surroundings, disregard sensor noise, and be secure without the human input.

The Navigation Challenge: State Estimation and Control

The flight autonomy system is justifiable and just estimates of the state. A UAV flight controller must have a real time approximation of six degrees of freedom (6-DOF): position (x, y, z) and attitude roll, pitch and yaw to stabilize the flight controller and self-control. The aerial platforms are also not stable like the ground robots who can stop their movement when they are not localized but rather an ad hoc mis-representation of state can cause the catastrophic crash of the aerial platform or may even a collision [5]. The solution deployed in navigation, must be rugged enough to take care of the rough resources of Size, Weight, and Power of the small UAVs. Fine grade navigational devices like a Ring Laser Gyroscopes (RLGs), a commercially available sensor in the aviation market, is excessively heavy and too much of power that does not fit the miniaturized dimensions of the electric drones. The developers are therefore using cheap consumer grade sensors and this presents high stochastic issues. The navigation problem is not just a location measurement problem, but an approximation of the actual location of the vehicle when sensor values are noisy and biased which in practically all cases are never continuous.

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Limitations of Single-Modality Sensing

There is no single sensor available that can meet any of the envelopes of autonomous flight in terms of safety and accuracy. Global Navigation Satellite Systems (GNSS) and Inertial Navigation Systems (INS that have been recognized as the two main pillars of conventional navigation have orthogonal strengths and weaknesses.

Vulnerabilities of GNSS

The standard of absolute positioning is GNSS (GPS, Galileo, and GLONASS). It offers non-divergent position and velocity error in the prolonged periods. Nonetheless, it is largely influenced by the environment to be reliable. Multi-path interference is observed in urban canyons (urban centers that have skyscrapers); here, satellite signals are reflected off the facades of buildings before reaching the receiver and cause errors of meters to tens of meters [6]. Moreover, the strength of GNSS signals at the surface of the Earth is very little, and it is prone to accidental Radio Frequency (RF) interference, malicious jamming or spoofing attacks [7]. Most importantly, where indoors and underground or under the dense trees canopy, GNSS is not available at all and thus which means that the UAV is blind when using satellite data alone.

Drift in MEMS Inertial Sensors

UAVs rely on onboard Inertial Measurement Unit (IMU) to cover gaps in the coverage of GNSS. IMU is a proprioceptive sensor, which can detect proper acceleration and angular rates at high frequency (usually 100 Hz to 1 kHz). Although external jamming is not a problem in MEMS-based IMUs, there are deterministic and stochastic errors such as thermo-mechanical noise, axis misalignment, and bias instability [8].

In a strapdown -based navigation system, acceleration is double-integrated to obtain position. This is a non-linear propagation of errors in a mathematical process; an error in accelerator measurement which is constant in value results in a position error whose value increases quadratically with time. A consumer grade MEMS IMU with no external correction will drift by hundreds of meters after one minute of flight [9]. Thus, free flight inertial navigation cannot support any mission longer than several seconds.

The Imperative for Sensor Fusion

To address these limitations, sensor fusion, the mathematical combination of sensory information provided by different sources has become a fundamental tool to the modern navigation stacks. Fusion algorithms can achieve a more accurate state estimate than the individual sensors by using the long-term stability of exteroceptive sensors (GNSS, Cameras, LiDAR, Magnets) with short-term precision of proprioceptive sensors (IMU) [10].

In the past, this has been done with the help of the Extended Kalman Filter (EKF), which linearizes the nonlinear equations of the UAV to forecast and correct errors of the state. But, with the transition of UAVs to more complex environments, the meaning of sensors has been broadened. Simultaneous Localization and Mapping (SLAM) algorithms have been used to integrate visual sensors (cameras) and Light Detection and Ranging (LiDAR) so as to enable UAVs to construct their own maps of unknown

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

surroundings to be used in relative navigation [11].

Scope and Objectives of Review

This paper that will seek to identify the critical analysis of autonomous UAVs navigation ecosystem. The gap between the hardware potential and the algorithm scheme as is the case with the outmoded surveys is bridged by the current paper since it only considers a single sensing modality or a filtering scheme. The objectives are to:
Talk about the principles of work and error models of central navigation systems (IMU, GNSS, Vision, LiDAR).
Polls of classical sensor fusion architecture (KF, EKF, UKF).
Discuss the Artificial Intelligence (AI) and Deep Learning as one of the actions to deliver the resiliency of the navigation in this instance, in the case of the GNSS-denied.
Create knowledge gaps in research and research domains to create Level 5 levels of autonomy in aerial systems.

Navigation Sensors for Autonomous UAVs

The ability of an autonomous UAV to navigate is limited, essentially based on the quality and variety of the sensory input into the UAV. These sensors give the raw measurements that allow to estimate the state of the vehicle (position, velocity, attitude (quaternion), and sensor biases). The most common classification of the navigation sensors is into proprioceptive sensors and exteroceptive sensors, the former measures the internal states relative to the vehicle frame, whereas the latter measures the state of the vehicle relative to the outside environment [12].

Inertial Measurement Units (IMU)

The essential element of any UAV flight control system is the Inertial Measurement Unit (IMU) that makes the Strapdown Inertial Navigation System (SINS). Since it is critical with Size, Weight, and Power (SWaP), Micro-Electro-Mechanical Systems (MEMS) technology is mostly employed in modern UAVs at the expense of precision when fiber-optic or ring-laser gyroscopes are used in manned aviation [13].

Accelerometers

The accelerometers used in MEMS are not coordinate acceleration measurement but proper acceleration measurement, or acceleration relative to a free-fall inertial frame. This implies that a ground stationary UAV will experience an acceleration of 1g (9.81 m/s2) of the ground normal force opposite to that of gravity.

$$a_{measured} = R_{wB}^{T}(a_w - g_w) + b_a + n_a$$

R_{wB}^{T} is the rotation matrix transforming gravity from world frame to body frame, b_a represents the bias, n_a represents the noise. The major error causes are instability of bias (flicker noise) and random walk of velocity (VRW). The cumulative effect of these errors as the result of the double integration results in position drift that increases quadratically with the time (error $\propto$ t2) [14].

Gyroscopes

Angular velocity (ω) is usually measured by MEMS gyroscopes by the Coriolis effect

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

acting on a vibrating mass.
Similar to accelerometers, gyroscopes have instability in bias and Angle Random Walk (ARW). An angular rate bias, integrated, will lead to an error in attitude, which increases linearly with time. This error in attitude causes the projection of the gravity vector to act incorrectly on the horizontal axes and makes the accelerator to assume the presence of linear acceleration to be the result of gravity, resulting in disastrous position excursion (error $\propto t3$) in seconds unless the error is corrected [15].

Global Navigation Satellite Systems (GNSS)
GNSS is a major source of absolute positioning to limit the drift of the IMU. Although GPS (USA) defines the most popular one, modern receivers are multi-constellation, which means that they can also track GLONASS (Russia), Galileo (EU), and BeiDou (China) at the same time. Such a variety of satellites enhances the observable satellites, which enhances the Dilution of Precision (DOP) in the obstructed conditions [16].

Positioning Modes
Standard Single Point Positioning (SPP): Makes use of pseudo-range measurements (time-of-flight of the signal). The maximum accuracy available is 2-5 meters as a result of atmospheric delays (ionosphere/troposphere) and ephemeris errors.

Real-Time Kinematic (RTK): The carrier phase of signal is used by RTK systems, and it has a wavelength of about 19 cm (L1 band). Using the signal received on the UAV and a fixed base station, the system may resolve the integer ambiguity, reaching a precision of centimeters (13 cm) [17].

Limitations
As one gets closer to the earth, the GNSS signals are extremely weak (lower than -160 dBW). They are readily dispersible on surfaces or plants and they are prone to the multipath interference with reflected pulses altering the time-of-flight measurement. Besides, the standard GNSS receivers (1-10Hz) are incapable of updating at the same rate to control agile quadrotor (high bandwidth control).

Vision Sensors
Computer vision offers rich semantic information of the surrounding, which allows visual odometry (VO), place recognition, and object tracking.

Monocular Cameras
The most efficient exteroceptive sensor is a single camera with SWaP-efficiency. Such algorithms as Monocular SLAM (e.g., ORB-SLAM) are based on the tracking of feature points in several frames. The inherent weakness of a monocular vision is the scale ambiguity; the system is unable to tell the difference between a large object in the distance and a small object in proximity without further sensor information (such as an IMU) to regain the metric scale [18].

Stereo Cameras

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

Stereo systems make use of two calibrated cameras with a given known distance between them. The depth (Z) is determined through triangulation by using the disparity. The disparity between corresponding pixels in the right and left images,

$$z = \frac{f.b}{d}$$

Stereo vision is used to offer absolute scale, but with wretched range (depth resolution scales with range) and exorbitant needs in computational complexity to generate dense disparity maps in real-time [19].

Event Cameras

A novel paradigm of optical sensing is event cameras (or Dynamic Vision Sensors). Event cameras, contrary to the conventional frame-based cameras which record images with a constant rate (e.g., 30 fps), contain independent pixels, which only emit an event in response to a change in the log-intensity of the pixel. This leads to microsecond latency, high dynamic range (HDR) and resistance to motion blur, which makes them best adapted to high-speed maneuvers of UAVs, even though they must be processed with special asynchronous algorithms [20].

LiDAR and Radar

Light Detection and Ranging (LiDAR)

LiDAR systems release laser bursts, and the Time-of-Flight (ToF) to calculate distance that create the accurate 3D point clouds.

Mechanical LiDARs: Spin a laser array 360 degrees. Although they have a large field of view, they are cumbersome and prone to mechanical breakdowns.

Solid-State LiDARs: Optical phased arrays or MEMS mirrors are used to do beam steering. They have a lower weight, are tougher, and are becoming popular in the small UAVs.

The most common mapping method is the LiDAR that is not always applicable in the conditions containing low optical reflectivity (e.g., glass buildings) or more substantial particulates (heavy rain/ fog) [21].

Radar

Radio frequencies in the millimeter-wave (mmWave) Radar work freely through fog, smoke, and dust (ex: 77 GHz). Relative velocity of objects can be directly measured using Doppler effect (Radar) as compared to LiDAR. Unlike LiDAR which has a generally better performance at radar angular resolution, Radar offers the required redundancy in desirable performance in bad weather [22].

Magnetometers and Barometers

Magnetometers

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Such sensors measure the local magnetic field vector to determine heading (yaw), which is not observable on the accelerator (measures the gravity) and is drifted on the gyroscopes. They normally employ the Hall effect or the anisotropic magnetoresistance (AMR). UAVs are well known to be challenging to calibrate with magnetometers because of hard-iron distortions (permanent magnets in speakers or motors) and soft-iron distortions (ferromagnetic materials in the frame) [23].

Barometers

Barometers are instruments that determine the altitude above the sea level by measuring the static atmospheric pressure and use of the hypsometric equation to determine altitude.

$$h \approx \frac{T_0}{L}[1 - (\frac{P}{P_0})^{\frac{RL}{g}}]$$

Although barometers are useful to measure relative altitude, they are susceptible to pressure transients (generated by wind gusts and the so-called ground effect (high pressure cushion) of the UAV rotors [24] themselves when flying close to ground, which might require the combination of barometers with ultrasonic or laser altimeters to make a landing.

Table 1: Comparison of Common UAV Navigation Sensors

Sensor Type	Measurand	Output Rate	Primary Advantage	Primary Limitation
MEMS IMU	Proper Accel, Angular Rate	High (1–8 kHz)	Self-contained, High Bandwidth	Unbounded drift, Bias instability
GNSS (SPP)	Position, Velocity	Low (1–10 Hz)	Global absolute reference	Signal occlusion, Multipath, Jamming
GNSS (RTK)	Position, Velocity	Low (1–10 Hz)	cm-level accuracy	Requires base station, High cost
Monocular Camera	Pixel Intensity (RGB)	Med (30–60 Hz)	Low cost, Semantic data	Scale ambiguity, Lighting sensitivity
Stereo Camera	Depth Map	Med (15–60 Hz)	Absolute scale, Passive sensing	Range limited by baseline; Computation heavy
Event Camera	Log-Intensity Change	Asynchronous	High Dynamic Range, No motion blur	Novel data structure, Low resolution

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

LiDAR	3D Point Cloud	Med (10–20 Hz)	High accuracy ranging	Heavy, Power hungry, Weather sensitive
mm Wave Radar	Range, Doppler Velocity	Med (10–20 Hz)	Robust in fog/dust/rain	Low angular resolution, Specular reflection
Magnetometer	Magnetic Field Vector	Med (50–100 Hz)	Yaw (Heading) reference	Sensitive to EMI (motors/currents)

Sensor Fusion Techniques

Sensor fusion refers to the mathematical integration of the various streams of non-similar data to create an optimal estimate of the vehicle condition of the vehicle. The objectives of autonomous UAV are to decrease the error covariance P and keep real time rates of processing. The fusion process may be regarded as a prediction-correction process, where the high-frequency internal sensors (IMU) with the state time are driving the state forward, and the external measurements (GNSS, Vision, LiDAR) are limiting the resulting drift [25].

Kalman Filter Family

Kalman Filter (KF) is the recursive optimal estimator of linear systems, where the noise is white and Gaussian. Nevertheless, due to the dynamics of UAVs, including complicated rotations and non-linear aerodynamic forces, the variants of the KF are needed, to retain the accuracy of the estimation [26].

Extended Kalman Filter (EKF)

The EKF is commonly regarded as a UAV-wide standard of navigation. It solves non-linearity by linearizing the system equations, and measurement models with the present mean and covariance using Jacobian matrices.

$$F_k = \frac{\partial f}{\partial x}\Big|_{\hat{x}_{k-1}}$$

In synchronous IMU-based systems, the EKF is helpful to integrate high-frequency data (at ~500 Hz) with lower-frequency exteroceptive data like GNSS or barometric pressure (~10 Hz). It is computationally efficient and in case the system encounters very non-linear maneuvering or the initial state estimate is incredibly inaccurate, it may be divergent [27].

Unscented Kalman Filter (UKF)

The UKF uses a deterministic sampling method called the Unscented Transform to counter the linearization errors of the EKF. It makes use of a set of sigma points which are solved by the actual non-linear equations and the mean and covariance are captured up to the third order of the Taylor series expansion. This renders the UKF more preferable when using high-dynamic flight profiles where linearization causes instability, but one must have additional onboard computational overheads [28].

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Complementary Filter

The Complementary Filter has a very strong alternative which may be applied in micro-UAVs with SWaP constraints and with an extremely small processing capacity, with processing power being frequency-domain instead of time-domain. It exploits the fact that gyroscopes are good at high frequency (although drifting over time) but accelerators are good at low frequency (but very noisy due to vibrations).

The mathematical expression of the filter is,

$$\theta_k = \alpha(\theta_{k-1} + \omega\Delta t) + (1 - \alpha)\theta_{acc}$$

where alpha is a gain that is usually adjusted to more than 0.9. It is not as statistically optimal as the KF in dealing with changing noise levels, but is simple and does not involve matrix inversions, thus is very effective on simple attitude heading and reference systems (AHRS) [29].

Visual-Inertial Odometry (VIO)

The VIO approaches are very close to employing visual data of cameras with an IMU inertial data. This is needed in the process of indoor or GNSS-denied navigation.

Filtering-based VIO: Such algorithms as the Multi-State Constraint Kalman Filter (MSCKF) store a list of prior camera poses as a history in the state vector and the system uses the observations of feature without including features in the state, which makes the algorithm much less costly to compute [30].

Optimization-based VIO: Other optimizers like the OKVIS (Open Keyframe-based Visual-Inertial SLAM) are a non-linear least-squares optimization that is run on a sliding window of keyframes. It is less sensitive to nonlinearities than EKF-based VIO but consumes more important CPU/GPU resources [31].

SLAM-Based Approaches

UAVs working under the conditions of unknown environments require Simultaneous Localization and Mapping (SLAM). SLAM is constructed as opposed to VIO which only monitors local motion.

Factor Graphs: The modern SLAM formulates the navigation task as a factor graph where each node represents a pose and each landmark, and each edge represents a constraint (the sensor measurements) (Albin 2014).

Loop Closure: One of the distinguishing features of SLAM is the possibility to recognize places visited already. In case of a loop which is detected, the algorithm conducts an overall optimization to rectify the drift that has been built up through out the trajectory [32].

AI and Deep Learning-Based Fusion

Recent studies have also moved towards data-driven approaches to manage sensor

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

properties that are not analytically modeling.

End-to-End Learning: These models are the direct conversion of raw sensor values (e.g. pixels) into control values. They are magnificent yet always not signed with safety guarantees.

Hybrid Deep Fusion: It can be strengthened by applying Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks to learn the non-stationary noise models that are complex and non-linear of MEMS IMUs. Deep learning also can be employed to detect and discard measurements that are outliers, e.g., GNSS multipath signals in urban canyons, before they can get to the main Kalman Filter [33].

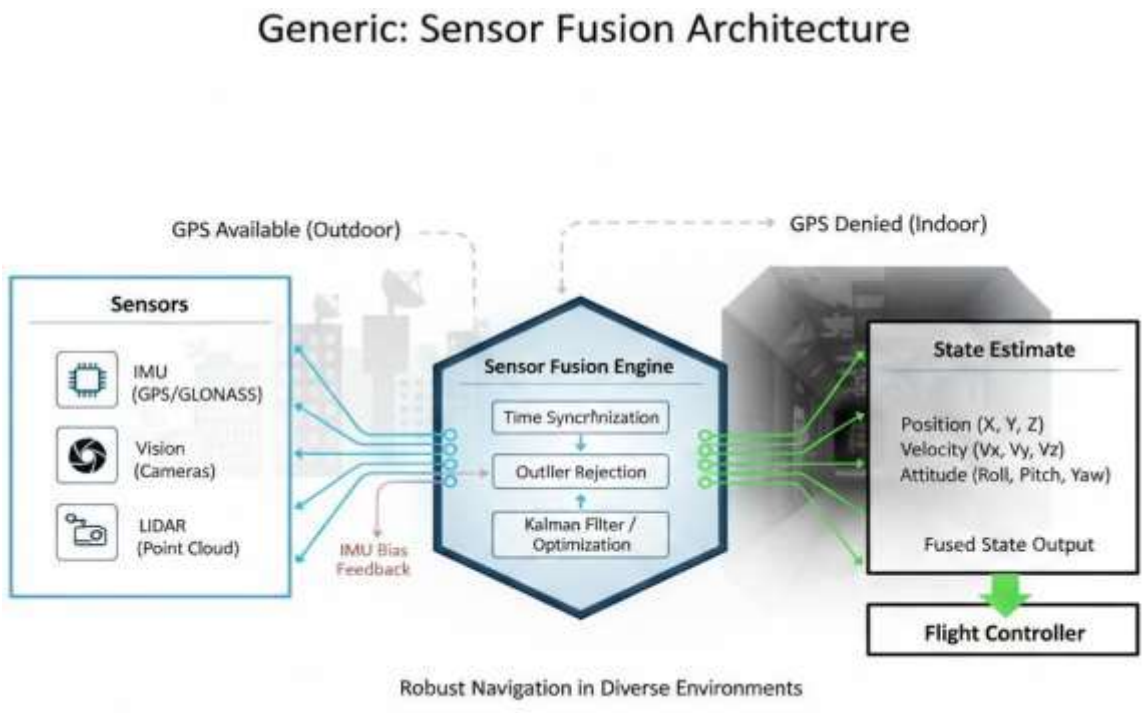


Figure 2: Show the generic sensor fusion architecture

Table 2: Comparison of sensor fusion algorithms

Algorithm	Computational Load	Non-Linearity Handling	Robustness to Outliers	Typical Use Case
EKF	Low	Medium (Linearization)	Low	Standard GPS/INS integrated navigation
UKF	Medium	High (Sigma Points)	Medium	High-dynamic flight and aggressive

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

				maneuvers
Complementary	Minimal	Low	Low	Low-cost AHRS and hobbyist drones
VIO (MSCKF)	High	High	Medium	Indoor autonomous flight, GNSS-denied ops
Graph SLAM	Very High	High (Optimization)	High	Autonomous exploration and 3D mapping
Deep Fusion	High (Training)	Very High	High	Complex urban environments with multipath

Challenges in UAV Navigation

Even with the massive theoretical and hardware breakthroughs in the field of aerial robotics, the realization of robust and fail-safe autonomy under real-world conditions is a complicated task. The subsequent paragraphs elaborate on the major technical bottlenecks that exist in the UAV research community at this point.

Sensor Noise, Drift, and Environmental Sensitivity

The dependency on MEMS that inertial is of critical vulnerability. Temperature variations are very sensitive to the sensors, any variation of temperature of air will result in non-linear changes in gyroscope and accelerator bias [34]. Moreover, the stability of the in-run bias of a sensor i.e. the change in bias of a sensor with a passage of time is constrained. Without GNSS and visual corrections, the priciest MEMS devices will add massively to horizontal and vertical position error and frequently will be incapable of operating within the safe operation range in narrow areas.

Navigation in GNSS-Denied and Challenging Environments

Although GNSS-denied navigation is an established science, there are still issues relating to its practical use in various settings.

Urban Canyons: Multipath interference is a so-called hidden threat, in which the receiver reports a high confidence and inaccurate position highly because of signal reflections.

Texture less Environments: Systems that depend on vision (VIO/SLAM) need unique visual elements in order to trace motion. The feature-tracking algorithms can simply

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

drop out in low-textured environments (e.g. white-walled corridors, darkened warehouses, or still bodies of water) [35].

Adverse Weather: LiDAR and optical cameras have a very short range because of scattering and occlusion by rain, snow, and fog that emphasizes the importance of using more resilient sensor modalities such as mm Wave radar.

Computational Latency and Real-Time Constraints

UAVs are unstable when it comes to oscillation frequency and rapid response. Flight controllers require update rates that are typically within the 400 Hz to 1 kHz range in order to guarantee the aerodynamic stability. However, the more advanced sensor fusion algorithms in particular, optimization-based SLAM and deep-learning-based perception algorithm are computationally heavy.

Dense 3D reconstruction and factor-graph optimization are now run in real-time, placing an overload on the computation. Since small UAVs with low-capability onboard processing (e.g. based on ARM-based microcontrollers) have trade-offs between the complexity of the fusion algorithm and the control loop latency, this may necessitate trade-offs between fusion complexity and control loop lag. The delay of the navigation estimate can lead to delay of the controller which can lead to erratic flight or crashes in the aggressive maneuver [36].

Environmental Dynamics and the "Static World" Assumption

The majority of classical SLAM and VIO systems follow the Static World assumption, according to which all the landmarks observed by the system are all stationary. In actual practices, though, UAVs tend to be in proximity to moving something like a pedestrian, vehicle or other drones. When a large percentage of the area covered by the sensor is occupied by the moving objects, the fusion algorithm might also incorrectly consider the specific motion to be that of the UAV itself resulting in large localization errors or odometry jumps [37].

Hardware Redundancy vs. Payload Constraints

Redundant sensor suites are necessary to ensure high levels of reliability (fault tolerance) in UAVs. Nonetheless, the introduction of the extra sensors adds weight and power consumption to the car, directly decreasing the flight range. The key design problem in autonomous systems is currently to find the "Pareto optimal" between redundancy of sensors, to guarantee safety, and payload efficiency, to guarantee longevity of the missions

Recent Advances and Research Trends

UAV navigation is now making a shift to the less geometric estimation to the so-called intelligent perception. This change is brought by the incorporation of high-performance edge computing and new sensing paradigms.

AI-Based Perception and Semantic Fusion

Old SLAM deals with geometry (lines and points), whereas in recent developments

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

there is Semantic SLAM. With the help of Convolutional Neural Networks (CNNs), the UAVs are capable of recognizing the objects (e.g., a chair, a tree, a window). This enables the fusion engine to give more importance on stable, non-moving landmarks to be located as opposed to dynamic ones, such as pedestrians [38]. Moreover, Deep IMU Denoising is an approach that predicts and cancels the vibration-based noise through the application of Long Short-Term Memory (LSTM) networks to MEMS sensors that is accurate enough to be used in tactical-grade devices.

Edge Computing and Onboard Intelligence

Dense navigation has been supported by the introduction of powerful System-on-Chip (SoC) architectures like the NVIDIA Jetson Orin and special purpose Vision Processing Units (VPUs). Real-time 3D reconstruction and simultaneous path planning is achievable through UAVs without ground station connection. They reduce the latency and guarantee that the vehicle is able to respond to the obstacle within milliseconds [39].

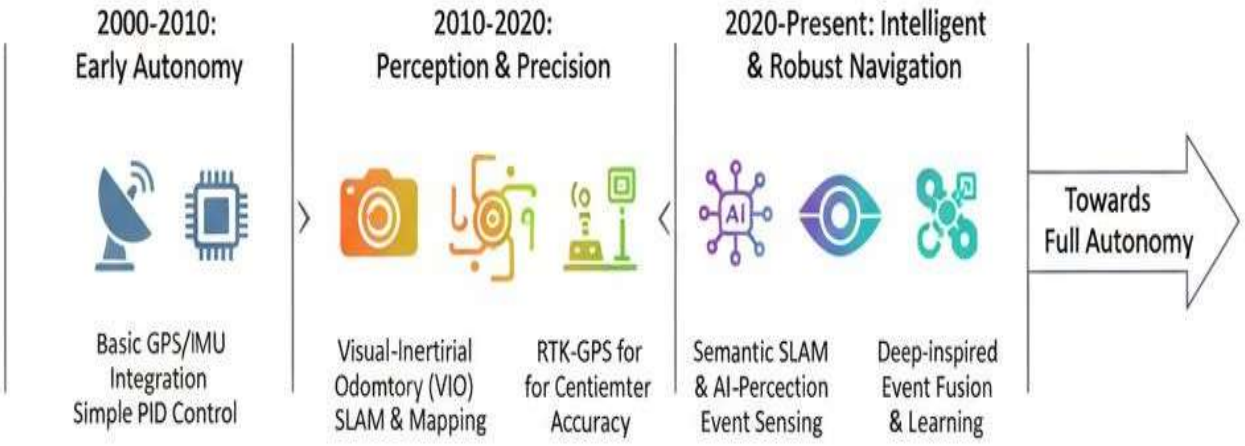
Multi-UAV Cooperative Navigation

Swarm Intelligence has created results on decentralized fusion algorithms in which various UAVs exchange their local estimates of state. A swarm may stay in its position within the world where one of the members is attached to an object of interest or an electronic signal, known as an anchor, and have the rest of the group follow it using Ultra-Wideband (UWB) ranging [40].

Future Research Directions

With the development of autonomous aerial systems, the industry is no longer concerned with simple state estimation but with the development of Level 5 autonomy, that is, the systems, which can work under any circumstances and do not need human control. The most critical frontiers into which to explore in the future would be the following.

Hybrid AI-Model-Based Fusion (Neural Kalman Filters)



Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 3 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

The drawback of the contemporary navigation is inevitably that it elucidates classical methods of

Figure 3: Evolution of UAV Navigation Technologies

computations of filters (EKF, UKF), is able to model Deep Learning models. The further enhancement is allocated to the so-called Neural Kalman Filters or Physics-Informed Neural Networks (PINNs). These architectures simply provide an extension of the Kalman Filters which is provided with deep layers of learners, which are being used to approximate non-linear transition model, or are being learned how to adjust noise covariance matrices (*Q* and *R*) in a real-time manner [41]. The control theory has been used to provide the predictability and safety assurances of its methodology, although the system can be exposed to unmodeled aerodynamic interactions such as slung-load dynamics or extreme wind shear.

Bio-inspired Navigation and Neuromorphic Sensing

The conventional computer vision is computationally expensive and has latency. The next generation UAVs may emulate the biological environment, in particular, the visual processing of Hymenoptera (bees and wasps) to navigate. Through imitation of the concepts of Optical Flow and Celestial Compass sensing, scientists expect to design low-energy neuromorphic systems, which process movement pixel-by-pixel. Combining Event-Based Sensors with spiking neural networks (SNNs) is expected to enable UAVs to achieve high-speed obstacle avoidance at a small fraction of the power consumption of the existing GPU-based systems [42].

Multi-Modal Fusion for Robustness in Extreme Conditions

The navigation suites used today are not suited to poor visual conditions (DVE) like smoke-filled buildings, heavy precipitation, or snow falls. The next generation studies should aim at the seamless, tight couple integration of atypical sensor modalities.

Thermal-Inertial Fusion: With the use of Long-Wave Infrared (LWIR) cameras to keep the localization in the total darkness or in the smoke.

Radar-Inertial Odometry (RIO): Designing algorithms to relying on millimeter-wave radar and go through the particulate matter that obscures LiDAR and optical cameras. The problem is to establish a common framework of fusion which allows dynamically reweighting these sensors, depending upon their perceived integrity or health in certain environmental conditions.

Resilient Navigation and Anti-Spoofing

Given the fact that UAVs are now regarded as the part of the critical infrastructure and defense, the threat of the GNSS jamming and spoofing has escalated. Autonomous Integrity Monitoring (AIM) must be added to the next generation navigation stacks. These algorithms give real time cross validation of the GNSS solution to the dead-reckoning solution of the VIO or LiDAR. When a mismatch is observed, as a marker of a spoofing attack, the system should be automatically transitioned to a state of Safety-of-Life, and may not be allowed to take any action to arrive safely at home or land other

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

than by relying on exteroceptive environmental characteristics [43].

Collaborative Swarm Localization and SLAM

Whereas the navigation of a single UAV is currently becoming strong, the next is Collaborative SLAM (C-SLAM). Decentralized optimization Future studies will examine how to use swarm of UAVs to distribute tiny sub-maps or feature descriptors through a wireless mesh network. A swarm can remove localization errors more rapidly than a single agent, and offer so-called distributed redundancy, in case the sensors of one of the drones are not functioning: a swarm can maneuver based on the relative positions of the neighbors [44].

Conclusion

The review has mentioned the necessity of navigation sensors and mathematical systems, which are required to integrate them to obtain autonomous flights of UAVs. The shortcomings of single sensing have led to the development of multi-modal architectures of Vision, LiDAR, and AI even though MEMS IMUs and GNSS remain the units. EKF and SLAM combination have taken UAV to open skies to the impossibility and inaccessibility of indoor environment via GNSS. The Level 5, autonomy bottlenecks have however been dynamic obstacles and real time latency issues. Hybrid structured UAV navigation will provide the future that has the statistical rigor of classical estimation and the environmental understanding of deep learning. It would make it even richer the fact that in the not so distant future swarms with pure autonomous UAVs would be deployed in unmapped hazardous areas, only days in the future.

Funding: This research received no external funding.

Data Availability Statement: No data set is used in this study.

Declaration Statement: The authors declare no conflicts of interest.

References

1. Shakhatreh H, Sawalmeh AH, Al-Fuqaha A, Dou Z, Almazaideh E, Guizani M. Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges. IEEE Access. 2019;7:48572-48634.
2. Radoglou-Grammatikis P, Sarigiannidis P, Lagkas T, Moscholios I. A compilation of UAV applications for precision agriculture. Computer Networks. 2020;172:107148.
3. Seo J, Duque L, Wacker J. Drone-enabled bridge inspection methodology and application. Automation in Construction. 2018;94:112-126.

Online ISSN 3007-3197
Print ISSN 3007-3189

4. Aurambout JP, Gkoumas K, Ciuffo B. Last mile delivery by drones: an estimation of viable market potential and access to citizens across European cities. European Transport Research Review. 2019;11(1):1-21.
5. Chao H, Cao Y, Chen Y. Autopilots for small fixed-wing unmanned air vehicles: A survey. 2010 International Conference on Mechatronics and Automation. IEEE; 2010. p. 3144-3149.
6. Groves PD. Principles of GNSS, inertial, and multisensor integrated navigation systems. 2nd ed. Boston (MA): Artech House; 2013.
7. Psiaki ML, Humphreys TE. GNSS spoofing and detection. Proceedings of the IEEE. 2016;104(6):1258-1270.
8. Woodman OJ. An introduction to inertial navigation. University of Cambridge, Computer Laboratory; 2007. Technical Report No.: UCAM-CL-TR-696.
9. Nassar S, El-Sheimy N. New approach for IMU stochastic modeling in GNSS/INS integration. Proceedings of the 18th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2005). 2005. p. 2215-2223.
10. Khaleghi B, Khamis A, Karray FO, Razavi SN. Multisensor data fusion: A review of the state-of-the-art. Information Fusion. 2013;14(1):28-44.
11. Cadena C, Carlone L, Carrillo H, Latif Y, Scaramuzza D, Neira J, et al. Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age. IEEE Transactions on Robotics. 2016;32(6):1309-1332.
12. Corke P. Robotics, vision and control: fundamental algorithms in MATLAB. 2nd ed. Cham: Springer; 2017.
13. Titterton D, Weston J. Strapdown inertial navigation technology. 2nd ed. Stevenage: The Institution of Engineering and Technology; 2004.
14. Salychev OS. Applied inertial navigation: problems and solutions. Moscow: BMSTU Press; 2004.
15. Oliver J, Curado C, Moura Oliveira P. MEMS IMU Error Modeling and Processing for UAV Navigation. Sensors. 2021;21(23):7921.
16. Kaplan ED, Hegarty CJ. Understanding GPS: principles and applications. 2nd ed. Norwood (MA): Artech House; 2006.
17. Teunissen PJ, Montenbruck O. Springer handbook of global navigation satellite systems. Cham: Springer International Publishing; 2017.

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

18. Scaramuzza D, Fraundorfer F. Visual odometry [tutorial]. IEEE Robotics & Automation Magazine. 2011;18(4):80-92.

19. Lazaros N, Sirakoulis GC, Gasteratos A. Review of stereo vision algorithms: from software to hardware. International Journal of Optomechatronics. 2008;2(4):435-461.

20. Gallego G, Delbruck T, Orchard G, Bartolozzi C, Taba B, Censi A, et al. Event-based vision: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2020;44(1):154-180.

21. Shan T, Englot B. LeGO-LOAM: Lightweight and Ground-Optimized Lidar Odometry and Mapping on Variable Terrain. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). 2018. p. 4758-4765.

22. Muhamad W, Pascoal A. Millimeter-wave radar for UAV navigation in GPS-denied environments. 2019 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE; 2019. p. 488-494.

23. Caruso MJ. Applications of magnetic sensors for low cost compass systems. Position Location and Navigation Symposium, IEEE 2000. 2000. p. 177-184.

24. Gronlund T, Rognvaldsson T, Jansson A. Barometer-based altitude estimation for UAVs using a ground effect model. 2012 IEEE International Conference on Robotics and Automation. IEEE; 2012. p. 3088-3093.

25. Khaleghi B, Khamis A, Karray FO, Razavi SN. Multisensor data fusion: A review of the state-of-the-art. Information Fusion. 2013;14(1):28-44.

26. Diez-Olivan A, Del Ser J, Galar D, Sierra B. Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. Information Fusion. 2019;50:92-111.

27. Huang G. Visual-inertial navigation: A concise review. IEEE International Conference on Robotics and Automation (ICRA). 2019; 9572-9582.

28. Julier SJ, Uhlmann JK. Unscented filtering and nonlinear estimation. Proceedings of the IEEE. 2004;92(3):401-422.

29. Mahony R, Hamel T, Pflimlin JM. Nonlinear complementary filters on the special orthogonal group. IEEE Transactions on Automatic Control. 2008;53(5):1203-1218.

30. Mourikis AI, Roumeliotis SI. A multi-state constraint Kalman filter for vision-aided inertial navigation. IEEE International Conference on Robotics and Automation. 2007; 3565-3572.

Online ISSN 3007-3197
Print ISSN 3007-3189

31. Leutenegger S, Lynen S, Bosse M, Siegwart R, Furgale P. Keyframe-based visual–inertial odometry using nonlinear optimization. The International Journal of Robotics Research. 2015;34(3):314-334.

32. Grisetti G, Kümmerle R, Stachniss C, Burgard W. A tutorial on graph-based SLAM. IEEE Intelligent Transportation Systems Magazine. 2010;2(4):31-43.

33. Chen C, Rosa S, Miao Y, Lu CX, Williams W, Markham A, Trigoni N. Selective Sensor Fusion for Neural Visual-Inertial Odometry. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019; 10542-10551.

34. Aggarwal S, Syed Z, El-Sheimy N. MEMS-IMU error modeling using the Allan variance method. Proceedings of the 21st International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2008). 2008. p. 202-208.

35. Scaramuzza D, Zhang Z. Visual-inertial odometry of aerial robots. Annual Review of Control, Robotics, and Autonomous Systems. 2020;3:101-125.

36. Falanga D, Kleber K, Scaramuzza D. Dynamic obstacle avoidance for quadrotors with event cameras. Science Robotics. 2020;5(40):eaaz9712.

37. Bescos B, Fácil JM, Netto J, Guerrero JJ, Neira J. DynaSLAM: Tracking, mapping, and inpainting in dynamic scenes. IEEE Robotics and Automation Letters. 2018;3(4):4076-4083.

38. Bowman SL, Atanasov N, Leighton K, Pappas GJ. Probabilistic data association for semantic SLAM. 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE; 2017. p. 1722-1729.

39. Mittal S. A survey on optimized implementation of deep learning models on the NVIDIA Jetson platform. Journal of Systems Architecture. 2019;97:428-442.

40. Cao Y, Yu WW, Ren W, Chen G. An overview of recent progress in the study of distributed multi-agent coordination. IEEE Transactions on Industrial Informatics. 2012;9(1):427-438.

41. Coskun H, Achilles F, DiPietro R, Navab N, Campaniello G. LSTM-KF: Learning a combined model of a Kalman filter and a recurrent neural network. arXiv preprint arXiv:2003.02700. 2020.

42. Liu X, Zhang J. A review of multi-sensor fusion algorithms for unmanned aerial vehicle navigation. Sensors. 2020;20(22):6667.

Online ISSN 3007-3197
Print ISSN 3007-3189

43. Coskun H, Achilles F, DiPietro R, Navab N, Campaniello G. LSTM-KF: Learning a combined model of a Kalman filter and a recurrent neural network. arXiv preprint arXiv:2003.02700. 2020.

44. Serres J, Ruffier F. Biomimetic navigation strategies for honeybee-inspired robots. Bioinspiration & Biomimetics. 2017;12(3):035006.

45. Morales JJ, Roysdon PF, Kassas ZA. Signals of opportunity aided inertial navigation. IEEE Control Systems Magazine. 2020;40(4):30-58.

46. Saeedi S, Trentini M, Seto M, Li H. Multiple-robot simultaneous localization and mapping: A review. Journal of Field Robotics. 2016;33(1):3-46.