AerospaceEurope Conference2021
WARSAW, POLAND | 23 -26 NOVEMBER 2021
PSAA
CEAS
Council of European Aerospace Societies

Data fusion concept for a sense and avoid system on-board small UAV

Michal Skowron-Nadulski[1], Janusz Narkiewicz[2]

[1] Łukasiewicz Research Network – Institute of Aviation
[2]Warsaw University of Technology

Abstract

In the recent years, significant progress in automation and machine learning was achieved allowing novel applications, also in aviation. Unmanned Aerial Systems are a segment of aviation industry benefiting from this progress.

The long-term objective of the research presented in this paper is to implement machine learning to sensor fusion for Sense and Avoid system on board of a small Unmanned Aerial Vehicle. The first part of the research is presented here during which various aspects of data fusion were investigated from a high-level perspective. Data fusion concepts were reviewed, which was a requirements formulation background for the specific system.

Keywords: sensor fusion, machine learning, uav, uas, sense and avoid

1. Introduction

In the recent years, a significant progress in machine learning (ML) methods was achieved, allowing various applications. For instance, in aeronautics ML algorithms were applied to predict engine failures [1] or optimizing operator flight routes [2].

An Unmanned Aerial System (UAS) is composed of an Unmanned Aerial Vehicle (UAV, supporting systems like control station and communication links and a personnel needed to control safe and efficient a mission execution [3], [4].

Several UAS definitions are used by research, industry, and academia; but the most crucial for a system design are those provided by institutional users like regulatory bodies [8],[9],[6] or military [7] users.

An UAV can be a fixed-wing airplane, rotorcraft (helicopter, tiltrotor, multi-rotor), airship, and an unconventional aircraft (like compound helicopters) of various weight and flying qualities.

UAS proved themselves in military operations (intelligence, reconnaissance, but also in battlefields) [5], they found significant commercial applications for surveillance, monitoring, transport [3], search and rescue (SAR), inspection of critical and noncritical infrastructure and many others.

The VLOS (Visual line of sight) or BVLOS (Beyond visual line of sight) may be executed, depending on the regulation bodies regulations. The FAA (Federal Aviation Administration, USA) requires flight to be performed within VLOS, where BVLOS requires formal waiver. The EASA (European Union Aviation Safety Agency) defines three operating categories: “open”, “specific” and “certified”. To operate in “open” category, a visual contact is required either by the remote pilot or by assisting UA observer [6]. While operating in “specific” and “certified” categories BVLOS flights can be permitted, and “certified” category will permit autonomous flights [7]. It is believed that once UAS acquire autonomous flights capabilities their potential will be fully utilised.

2. Data fusion for sense and avoid systems

Autonomous operations require specific functionalities like [8]:

- Sense and Avoid (SAA) systems, to prevent collision with static and moving objects.
- Reliable communication to link the platform and the ground station, as the robust data and information exchange are crucial for safety of the UAV during operation.
- Safe and efficient traffic control to supervise many UAV by reduced number of operators, including taking over a mission control in case of emergency,
- Embedding UAS into an airspace supervised by Air Traffic control services or an uncontrolled one, which needs for instance standardization of data exchange.

Standardization of UAS design and manufacturing processes and operations should lead to generally accepted standards. A proliferation of good practices from aeronautical sector to other entities involved in UAS production and operation would be beneficial.

Without human operator on board (now), and without operator on-ground (in future), UAS need autonomously sense and avoid any intruders and obstacles to keep safe separation from other air traffic participants, to mitigate collision threads [8] with both static (like power lines or buildings) and mobile (as other air traffic) obstacles.

The main SAA functionalities [9] reflect:

- sensing - to monitor surrounding environment using efficient scanning techniques to provide data for detecting
- detecting - using data from sensors to detect obstacles in the monitored space and assessing a threat of collision
- avoiding - to mitigate potential collision by developing and executing avoidance strategy.

The SAA configurations with GCS autonomous functions or human operator in the decision loop are short-term solutions. The on-board autonomy for sensing, detecting, and avoiding are the final objectives, as fully autonomous sense and avoid systems are not yet available. [9]

Efficient sensing capabilities cannot be obtained by only one type of sensor, as it may not provide enough data for complete situation awareness, so combination of data from multiple sensors is needed. Data fusion methodologies are the key elements of SAA systems [10] to increase robustness of detection and elaborate decision to collision avoidance.

3. Data fusion concepts

A data fusion is a new concept, so there is no its commonly accepted definition. For instance, data fusion is defined [11] as “[the study of] efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making”.

Data fusion may be considered from the level of sensor signal processing [12] (Figure 1):

- Sensor level (low-level) – data from sensors is combined directly at signal processing level,
- Feature level (medium-level) – sensor data is processed to produce information,
- Decision level (high-level) – various information is combined to enrich the background for resultant decision.

Where data, information and decisions are defined as:

- Data is the most basic information obtained from the sensors signals, sensors outputs are converted into data which are transmitted for further processing,
- Information (also called feature) is a useful, required information resulting from data processing this might be size, visual representation, trend information, speed, movement vector and many more,
- Decisions are hypothesis about the situation resulting from analysing information on observed phenomena features or prior decisions [13].

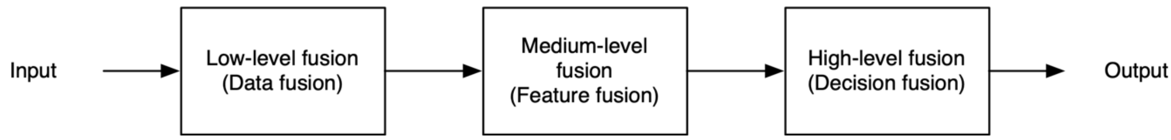

Figure 1. Dependencies between input and output of different level fusion

Evaluation of data fusion efficiency may be done considering [14] “behaviour of a data fusion system operated by various algorithms and comparing their pros and cons based on a set of measures or metrics”. This approach covers assessing impact of data quality on fusion efficiency, as well as performance of algorithms of sensor fusion. Not many of the surveyed works studied performance evaluation process of integrated system from practical perspective. Usually, validation was done in simulated scenarios, but very often not within realistic flight envelope. However, the right performance criteria are important to validate implemented data fusion solution, covering metrics of performance (like computational time or ability to detect danger with adequate margin) and algorithm applicability and sufficiency in UAS SAA scenarios. Such criteria may be established using existing methods and best practices.

Data fusion in SAA may be considered from such perspectives as:

- frameworks covering relations between subsystems,
- topology of data acquisition and processing,
- functional relations between sensor data,
- data and/or information at input and at output.

To present data fusion concepts within SAA systems composed of several sensors formal frameworks may be used to describe data and information flow hardware components. The frameworks may be classified within three groups [15]:

- Abstract models which are hardware and software agnostic and show general overviews of systems,
- Rigid frameworks, which provide information sufficient to implement the fusion algorithms,
- Generic frameworks, which are intermediate level between abstract models and rigid frameworks, containing information about hardware or software selection, however providing not enough information to implement it.

A framework proposed in 1986 [16] [17] is presented in Figure 2.

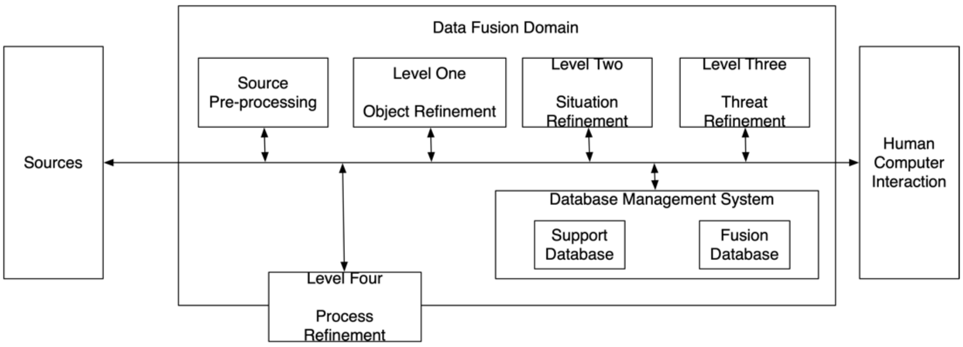

Figure 2. An example of data fusion framework [16]

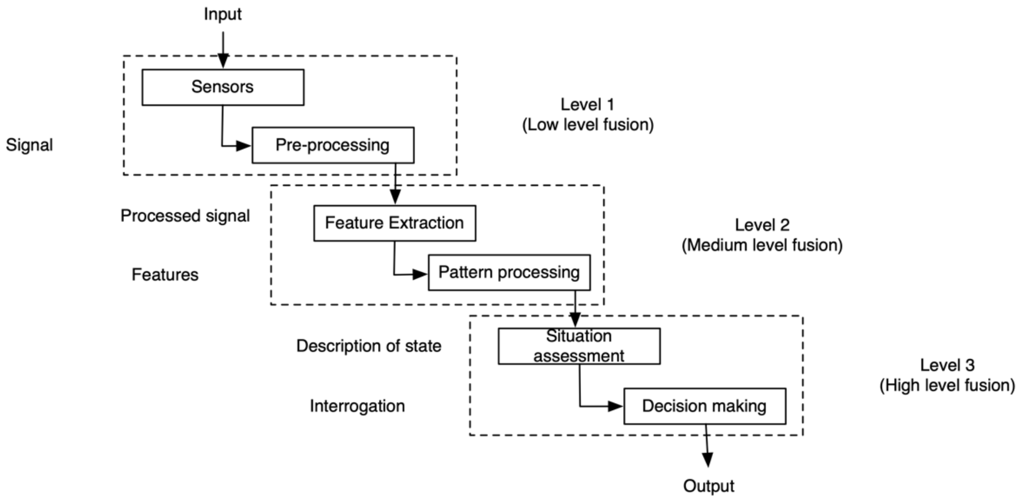

Figure 3. Waterfall type framework (based on [17])

A waterfall framework presented in Figure 3 illustrates data / information flow between the subsequent levels of data fusion; levels 1, 2 and 3 are considered as low, medium, and high-level fusion respectively.

A framework, based on avionics applications (Figure 4) covers only two layers: hardware containing computational platform and sensors and software i.e., computing programs running at the computational platform including:

- acquisition and pre-processing of sensor data (standardization, outlier detection, etc.),
- generation of information needed for detection and avoidance,
- data transfer to on-board systems or/and to operators.

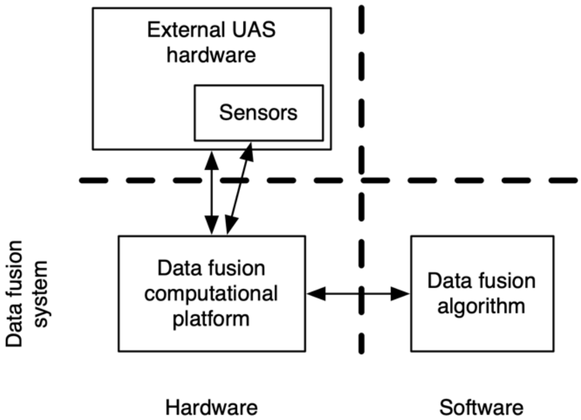

Figure 4. Data flow between data fusion and external systems

A system topology (also called architecture) describes process of converting raw data to useful information, which according to [18] may ne centralized, decentralized, distributed or hierarchical topology (Figure 5 and Figure 6).

In a centralized topology, each sensing node transmits data to the single central processing unit. A centralized topology usually provides good performance when raw sensor data are aligned (compatible in terms of time and format), but it is not resilient to failures, as a single node malfunction or deterioration of communication between nodes may cause information lags and/or fusion errors. [18].

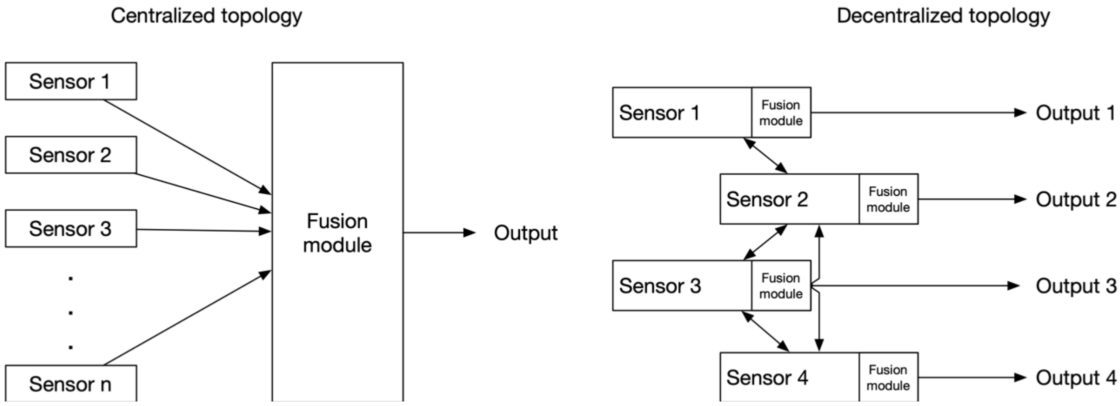

Figure 5. Examples of centralized and decentralized topology fusion system

In a decentralized architecture sensing nodes execute part of data fusion locally, also using data / information transferred from their peers. A decentralised system may not collapse after a single node failure; hence it is more resilient to a centralized one. However, its performance might be diminished by a redundant information processing, by cost of data transfer between the nodes or by data transfer deterioration [19].

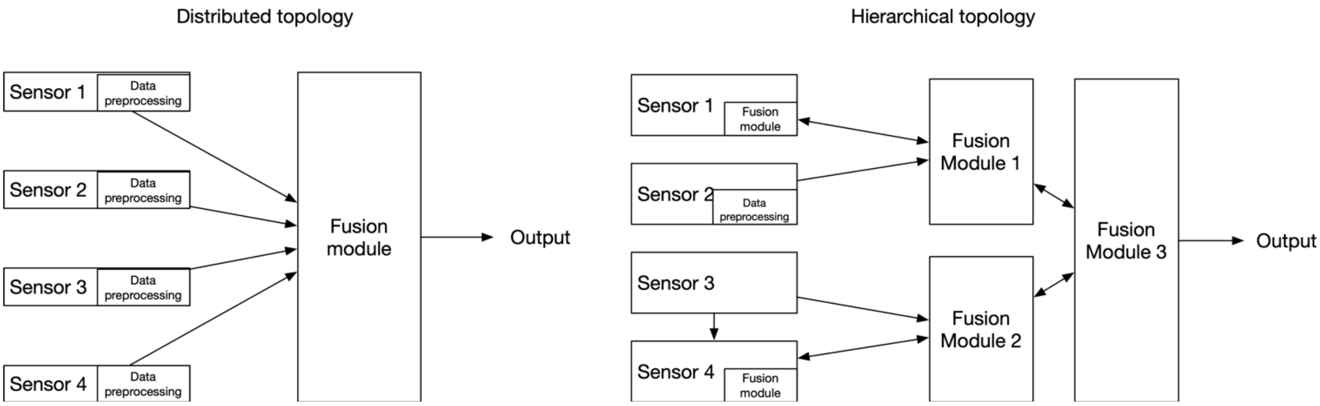

Figure 6. Examples of distributed and hierarchical topology fusion system

The distributed topology combines centralized and decentralized structures. A part of the data is processed locally at the nodes. The results are transferred to other nodes for subsequent processing. [19]. Compared to a decentralized structure a distributed technology may require less data transfer between the nodes, but it is more prone to failure data acquisition and processing nodes.

A hierarchical topology combines structures of centralized and decentralized topologies. It has several intermediate data processing levels, which may lead better reliability, but increasing computation, data transfer and implementational costs are higher.

Functional relations between sensor data at different fusion levels (data, feature, or decision) are given in Table 1 [20] [19], which being hardware and software agnostic may provide guidance for sensors selection to assure redundancy.

Type name	Data functional relation	Data redundancy	Fusion example
Complementary	Data provided different (complementary).	Augmenting obtained data, improving information.	Two RGB cameras capturing different part of scene providing wider field of view.
Competitive	Data sources provide information on the same feature.	Fault detection and isolation, redundancy for data input failure	Two GNSS receivers providing simultaneously platform position for providing redundancy.
Cooperative	Data sources are combined to obtain information which is not available from individual data source.	Augmenting obtained data. Novel information	Combination of RGB camera and LIDAR, RGB provides image of the scene, LIDAR provides distances to various objects. information. Combined information is richer.

Table 1. Functional relation between the data

The categorization of fusion data processing proposed in [21] was based on system input and output relations considering data sensor, feature, or decision level. *Data-in - Data-out (DAI DAO)* is the direct relationship between input ("raw data") and output ("data partly processed"). It is often applied to combine data from various sensors measuring the same physical quantity or the same type of sensors but of different operation principles. *Data-in - Feature-out (DAI - FEO)* describes algorithms fed by data and producing features. An example of such fusion is an object recognition on images captured by RGB cameras. *Feature-in - Feature-out (FEI FEO)* algorithms process features, so they are named as feature fusion. They are applied for instance to reduce dimensions of the feature space which is convenient from computational efficiency. *Feature-in Decision-out (FEI DEO)* algorithms provide decisions form features as input data. An example of such algorithm is object recognition base on features describing surrounding. *Decision-in Decision-out (DEI DEO)* algorithms named decision fusion are the highest level of sensor fusion.

4. System functional requirements

The main objective of UAS is to successfully complete the mission. To achieve it autonomously, UAS must possess "the capability to see, sense or detect conflicting traffic or other hazards and take the appropriate action" [22], which may be named Sense and Avoid (SAA) system, which may be composed of components performing different functionality defined by high-level requirements (Figure 7).

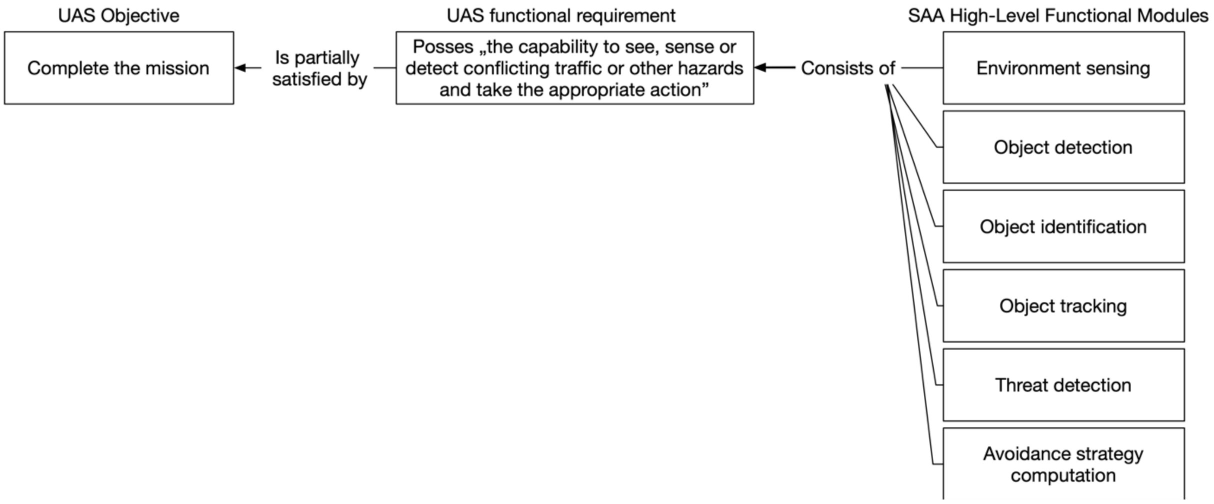

Figure 7. Example of UAS SAA requirement breakdown

The functions of SAA components and data flow is illustrated in Figure 8.
.

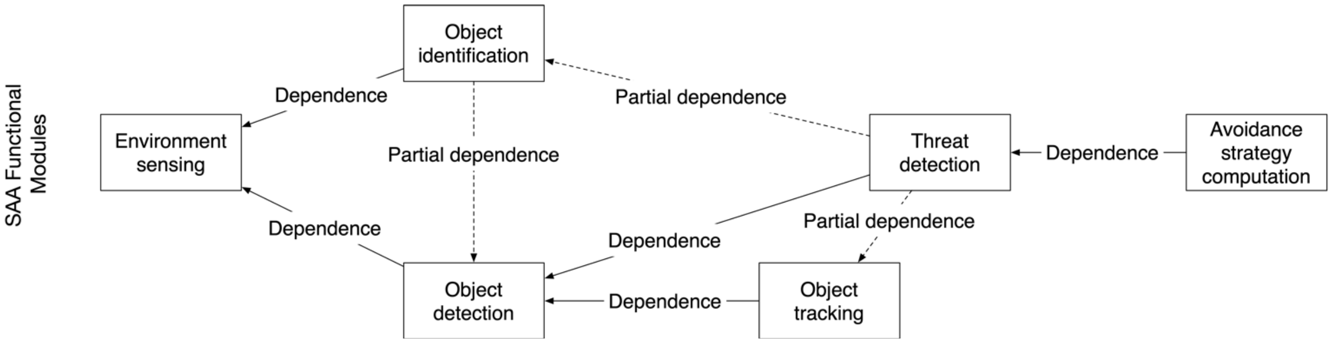

Figure 8. Data flow between SAA system components

In this research "Object detection" and "Object identification" modules are being developed. For these components high-level requirements are defined, while "Environment sensing" are used only as sources of additional data needed. The high-level requirements for the developed components are illustrated in Figure 9.

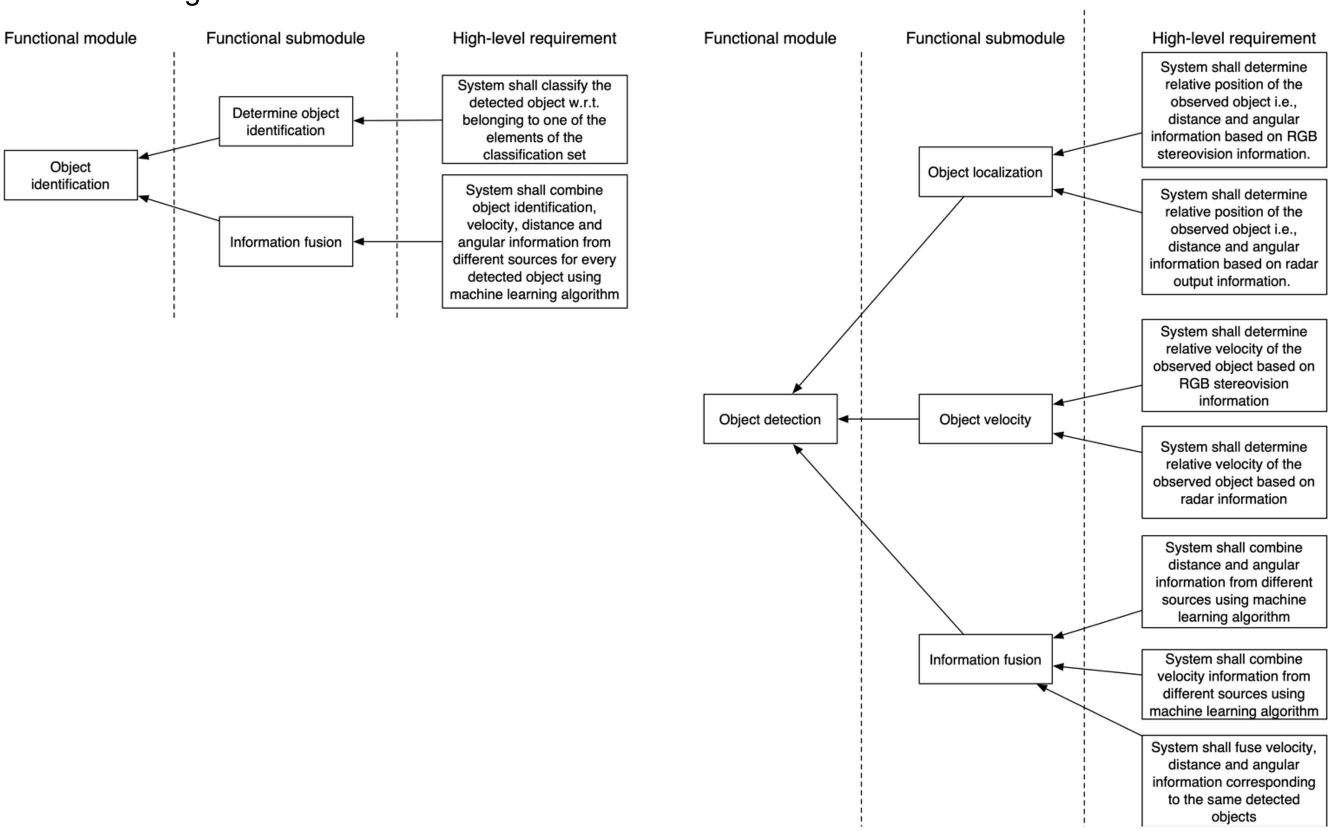

Figure 9. High-level requirements for "Object identification" and "Object detection"

The proposed system architecture for combined modules is presented in Figure 10. The data fusion system will contribute to the main UAS mission providing information enhancement. The hardware, software redundancy is included. Defining performance metrices is not essential at this stage of development but it should be done during the development process. The requirements should also be derived for the system operation, such as:

- detection area is the scene observed in the direction of UAV flight,
- size of detected objects is bounded by the small size drone,

- only on-board sensor and computational resources are applied.

The specific requirement for the components is formulated based these high-level requirements for SAA.

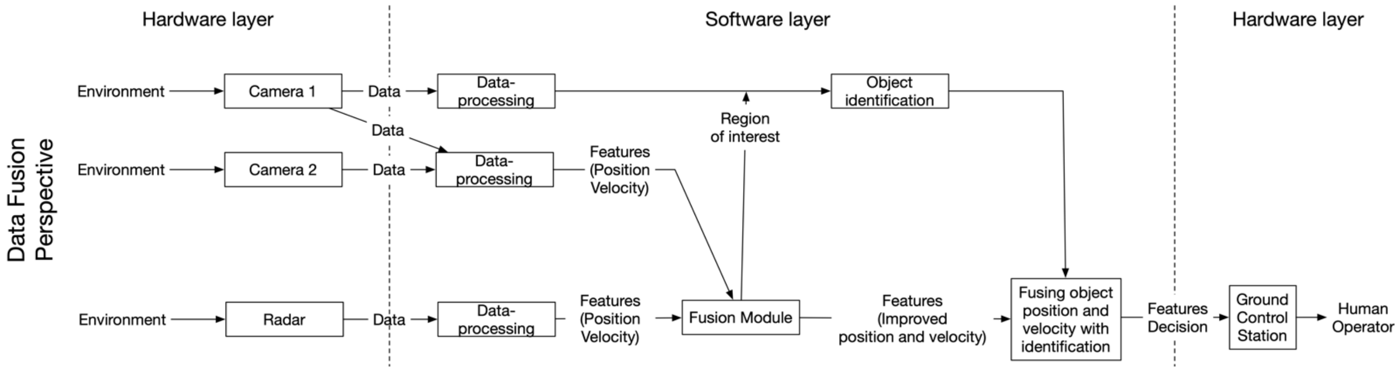

Figure 10. System architecture for on-board object detection for small UAS

5. Summary

The UAS autonomous operations are believed to be a key to enable its full potential. Several problems should be solved, one of which is to achieve “see-and-avoid” (SAA) capabilities. A SAA system can be conceptualized into three functional layers: sensing, detecting, and avoiding. Various data fusion concepts and its connection with SAA system were considered in the paper (formal frameworks, topology, functional relation between data and input and output of data or information), which provided guidance and starting point for designing data fusion algorithms for SAA functionality.

6. Contact Author Email Address

Michal.skowron@ge.com

7. Copyright Statement

References

[1] W. Yan, “Application of Random Forest to Aircraft Engine Fault Diagnosis,” in *The Proceedings of the Multiconference on "Computational Engineering in Systems Applications"*, Beijing, China, 2006.

[2] R. Marcos, O. García-Cantú and R. Herranz, “A Machine Learning Approach to Air Traffic Route Choice Modelling,” *arXiv preprint arXiv:1802.06588,* 2018.

[3] N. Aswini, E. Krishna Kumar and S. Uma, “UAV and obstacle sensing techniques – a perspective,” *International Journal of Intelligent Unmanned Systems,* vol. 6, no. 1, pp. 32-46, 2018.

[4] M. Skowron, W. Chmielowiec, K. Glowacka, M. Krupa and A. Srebro, “Sense and avoid for small unmanned aircraft systems: Research on methods and best practices,” *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering,* vol. 233, pp. 6044-6062, 2019.

[5] S. Gupta, M. Ghonge and P. Jawandhiya, “Review of Unmanned Aircraft System (UAS),” *International Journal of Advanced Research in Computer Engineering & Technology,* vol. 9, 2013.

[6] Federal Aviation Administration, “Summary of Small Unmanned Aircraft Rule (Part 107),” 21 06 2016. [Online]. Available: https://www.faa.gov/uas/media/Part_107_Summary.pdf. [Accessed 10 04 2021].

[7] EASA, “Certified Category - Civil Drones,” [Online]. Available: https://www.easa.europa.eu/domains/civil-drones-rpas/certified-category-civil-drones. [Accessed 10 04 2021].

[8] Federal Aviation Administration, “Unmanned Aircraft Systems (UAS) Traffic Management (UTM) Concept of Operations,” 2018.

[9] G. Fasano, D. Accado, A. Moccia and D. Moroney, “Sense and Avoid for Unmanned Aircraft Systems,” *IEEE Aerospace and Electronic Systems Magazine,* vol. 31, pp. 82-110, 2016.

[10] J. Kocić, N. Jovičić and V. Drndarević, “Sensors and Sensor Fusion in Autonomous Vehicles,” in *2018 26th Telecommunications Forum (TELFOR)*, Belgrade, 2018.

[11] H. Boström, S. Andler, M. Brohede, R. Johansson, A. Karlsson, J. van Laere, L. Niklasson, M. Nilsson, A. Persson and T. Ziemke, “On the Definition of Information Fusion as a Field of Research,” Institutionen fö kommunikation och information, 2007.

[12] R. C. Luo, C. C. Chang and C. C. Lai, “Multisensor Fusion and Integration: Theories, Applications, and its Perspectives,” *IEEE Sensors Journal,* vol. 11, no. 12, pp. 3122-3138, 2011.

[13] B. Waske and J. A. Benediktsson, “Decision Fusion, Classification of Multisource Data,” in *Encyclopedia of Remote Sensing*, New York, NY, Springer New York, 2014, pp. 140--144.

[14] B. Khaleghi, A. Khamis, F. O. Karray and S. N. Razavi, “Multisensor data fusion: A review of the state-of-the-art,” *Information Fusion,* vol. 14, no. 1, pp. 28-44, 2013.

[15] W. Elmenreich, “A review on system architectures for sensor fusion applications,” in *IFIP International Workshop on Software Technolgies for Embedded and Ubiquitous Systems*, 2007.

[16] F. E. White, “Data Fusion Lexicon,” The Data Fusion Subpanel of the Joint Directors of Laboratories Technical Panel for C3, San Diego, 1991.

[17] D. Hall and J. Llinas, “An Introduction to Multisensor Data Fusion,” *Proceedings of the IEEE,* vol. 85, no. 1, pp. 6-23, 1996.

[18] H. B. Mitchell, Data fusion: concepts and ideas, Springer Science & Business Media, 2012.

[19] F. Castenado, “A Review of Data Fusion Techniques,” *The Scientific World Journal,* vol. 2013, 2013.

[20] H. F. Durrant-Whyte, “Sensor models and multisensor integration,” *The International Journal of Robotics Research,* vol. 7, no. 6, pp. 97-113, 1988.

[21] B. V. Dasarathy, “Sensor fusion potential exploitation-innovative architectures and illustrative applications,” *Proceedings of the IEEE,* vol. 85, no. 1, pp. 24-38, 1997.

[22] North Atlantic Treaty Organization, “NATO Standard AEP-101 Guidance on Sense and Avoid for Unmanned Aircraft Systems,” NATO Standarization Office (NSO), 2017.

[23] International Civil Aviation Organization, “Unmanned Aircraft Systems (UAS),” International Civil Aviation Organization, Montreal, 2011.

[24] Civil Aviation Authority, “Glossary,” 31 07 2019. [Online]. Available: https://www.ulc.gov.pl/en/unmanned-aircraft/4669-glossary. [Accessed 09 04 2021].

[25] European Union, “Easy Access Rules for Unmanned Aircraft Systems(Regulations (EU) 2019/947 and (EU) 2019/945),” 2021.

[26] M. Liggins II, D. Hall and J. Llinas, Handbook of multisensor data fusion: theory and practice, CRC Press, 2017.