# Computational Intelligent Algorithms in Multi-Sensor Data Fusion for UAV Detection and Identification: Challenges and Opportunities

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## Abstract

Nowadays, counter-Unmanned Aerial Vehicle (c-UAV) applications include multisensory devices, such as electro-optical, thermal, acoustic, radar and radio frequency sensors, the data of which can be combined to increase confidence in hazard identification. Object identification, classification, multi-object tracking, and multisensory information fusion are just a few of the complex challenges that occur as a result. In recent years, researchers have made significant progress using deep learning-based approaches to accomplish similar tasks for generic objects, but using deep learning for UAV detection and classification is a new idea. Consequently, there is a need to offer an overview of deep learning technologies applied to c-UAV related tasks using multisensor data. The significant increase in the number of articles on "c-UAV systems" in recent years shows that research in this area still has enormous opportunities. This paper aims to describe improvements in deep learning on c-UAV-related tasks when applied to data from multiple sensors and multisensor information fusion and make recommendations for using deep learning algorithms in UAV detection and identification.

**Keywords:** UAV; Multisensor Data Fusion; Deep Learning; UAV detection; UAV identification.

## 1 Introduction

Unmanned Aerial Vehicles (UAV), or as they are often referred to unmanned vehicles, are used by government authorities for tasks from border security, law enforcement, surveillance area, and forest fire surveillance to commercial-related studies used by civilians such as construction, agriculture, insurance, internet communications, and general cinematography. A recent advance is the counter UAV (c-UAV) system, which offers a system(Prime Consulting & Technologies, 2015) consisting of multisensor weaponry to maintain situational awareness and protect critical infrastructure or critical events. This application includes several integrated sensors for detecting threats, mainly through radar or electro-optical/thermal (EO-IR) sensors and less often through acoustic and radio frequency (RF) sensors.

However, the rapid deployment of UAVs poses serious security concerns. In recent years, newspapers and mass media have reported dozens of incidents involving UAVs flying in restricted areas and around critical infrastructure or public events. Research efforts on UAV detection and classification methods based on deep learning using radar, electro-optical, thermal, and acoustic sensors, as well as multisensor information fusion algorithms, have been thoroughly reviewed. Research on c-UAV systems is an emerging field, and the addition of deep learning could lead to breakthrough in the years to come.

A considerable drawback in multisensor C-UAV applications is that the information from the different sensors is not combined to get the results. However, the warning signals are used independently of each system component to provide some initial warning which the human operator then confirms. For example, early detection emanating from a radar sensor is then confirmed by an operator looking in this direction via optical cameras. The latest advances in data fusion techniques can fully automate without a substantial trade-off in classification capabilities. Data fusion techniques have garnered significant attention in recent years, mainly because of the importance of combining information from different types of sensors for various applications(Liggins, Hall, & Llinas, 2009). The scope of the data pooling target is to achieve more accurate results than those from a single sensor while compensating for each other's weaknesses.

On the other hand, artificial intelligence and deep neural networks (DNN) have become desirable methodologies for data representation(Zhao, Zheng, Xu, & Wu, 2019). DNN is used to process various kinds of data from multiple sources because of its ability to find high-level and abstract features that feature extraction methods cannot. Therefore, the use of deep learning methods in data fusion can be significant in overcoming the critical problem of multisensor data aggregation(Samaras et al., 2019).

One of the foundations of current information technology is sensor technology. Sensors play a crucial role in data fusion systems and are an essential component of them. Function, structure, and other factors can be used to represent data fusion. The functional model is the most important from the standpoint of the data fusion process. It explains the data fusion system's critical operations as well as its subsystems. It outlines the basic procedures of the data fusion system and its subsystems, the database's role, and how the system's components interact. The structural model explains the data fusion system and the information interaction process between the design and the external environment from a data flow perspective (Chang & Ko, 2014)(Yu, 2017). Figure 1 depicts the multisensor data fusion system's functioning model(Ma, Zhang, Wang, & Zhang, 2018).

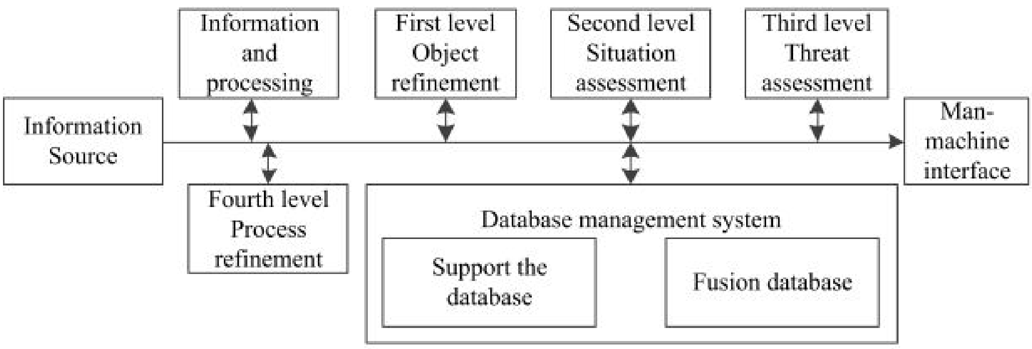


**Figure 1. The functional model of multisensor fusion system**(Ma et al., 2018)

Data fusion systems are frequently complicated mixes of sensing devices, processing, and fusion algorithms. This paper provides an overview of the basic principles in data fusion architecture, both from a hardware and algorithm standpoint. The essential difficulties of sensing, estimation, and perceiving are addressed through data fusion applications in robotics.

Multisensory data merger is a technique for combining data from multiple sources to create a cohesive image. Sensor networks, robotics, video and image processing, and intelligent system design are just a few domains where data fusion systems are frequently used. Because data fusion is such a vast topic, numerous phrases have been thrown around. This ad hoc terminology and approaches across various sciences, including engineering, management, and a variety of other publications, demonstrate that the same idea has been investigated numerous times. In recent years, the data fusion research community has made significant progress. The flawless emulation of the human brain's data fusion potential, on the other hand, is still a long way off(Durrant-whyte & Henderson, 2008). This paper aims to describe improvements in deep learning on c-UAV-related tasks when applied to data from multiple sensors and multisensor information fusion and make recommendations for using deep learning algorithms in UAV detection and identification.

## 2 Methodology

The description of this research process must be backed up with references for the explanation to be scientifically acknowledged. In 2004, research on UAV sensor data fusion algorithms began, which has since been published in many scholarly journals(Mahler, 2004). Meanwhile, in 2009 researchers began investigating UAV detection using multisensor data fusion techniques(Yi & Min, 2009).

### 2.1 Kalman Filters + Multi-Layer Perceptron (MLP)

One of the multisensor data fusion methods is Safari et al. (Safari, Shabani, & Simon, 2014). In this paper, data fusion problems for asynchronous, multirate, and multisensor linear systems are studied. Several sensor systems observe the linear system, each having a different sampling rate. Assuming that the state-space model is known at the highest time resolution of sensor system scale and a known mathematical relationship between sampling rates, a comprehensive state-space model covering all sensor systems is presented. The state vector is estimated by a neural network that combines the outputs of several Kalman filters, one filter for each sensor system. State approximation proved to perform better than other data fusion approaches due to the new neural network-based sensor fusion approach.

Figure 2 depicts the MLP, in which N Kalman filters are used, one for each sample rate. As demonstrated in, each Kalman filter produces M state estimates. These MN estimations are sent to a set of hidden neurons through the MLP, with the number of hidden neurons specified by the designer as a tuning parameter. The output neuron receives the hidden neurons' outputs, and the MLP's output is the fused state estimate based on the highest sampling rate.

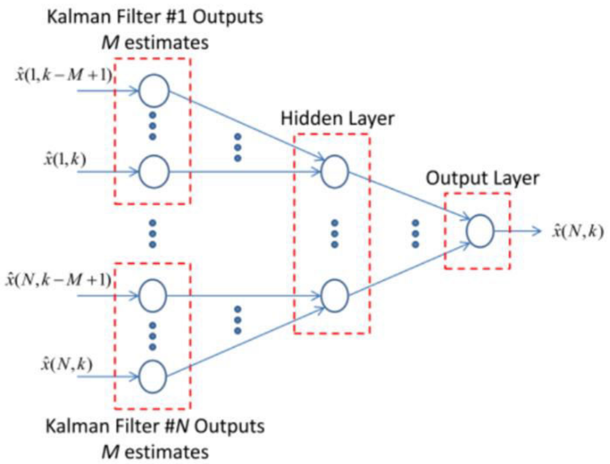


**Figure 2. Multilayer perceptron for fusing Kalman filter estimates. There are N sensor systems in this figure, and thus N sets of Kalman filter estimate. Each set of Kalman filter estimates includes M estimates. This MLP has MN inputs, a user-determined number of hidden neurons, and one output.**

## 2.2 Clustering Algorithm

This algorithm presents a new hybrid algorithm for clustering and cluster member selection in a wireless multisensor system. After the passage of the cluster head and member nodes, a data fusion technique is proposed to partition and process the data. The proposed scheme efficiently reduces blind broadcast messages but also reduces signal overhead due to cluster formation. Furthermore, routing techniques are provided based on the layered architecture. The proposed layered architecture efficiently minimizes the routing path to the base station. A comprehensive analysis was carried out on the proposed scheme with advanced centralized and distributed clustering techniques. These results show that the proposed system outperforms competitive algorithms in terms of energy consumption, packet loss, and cluster(x) formation(DIn, Ahmad, Paul, Ullah Rathore, & Jeon, 2017).

In the clustering technique, a set of devices are grouped in a geographic area. After grouping, the cluster head is selected based on specific algorithms, where the selected node is called the cluster head, while the other nodes are called member nodes. The cluster head obtains data from its member nodes and combines them. It then forwards the data to the neighboring cluster heads at the base station via direct hop or multi-hop. The routing data in the cluster is divided into two broad categories, namely intra-cluster (within the same group) and inter-cluster (within the set) data transmission. Such a cluster layout reduces a large amount of energy in the network. Wireless ad-hoc and sensor networks consist of hundreds or even thousands of nodes that communicate with each other. Nature is so densely networked, consumes more energy in exchanging data, with unstable additive loads and fatal errors.

After the formation of the cluster, then we have to process the Big Data received by the cluster head. The proposed architecture is based on data fusion, which was initially developed by the Director of the US Joint Laboratory (JDL) and the US Department of Defence (DoD) (Sorsa, Koivo, & Koivisto, 1991). The researcher has modified and changed the existing data fusion techniques according to the scheme based on the architectural requirements. The block diagram of data fusion in a multisensor system is illustrated in figure 3.

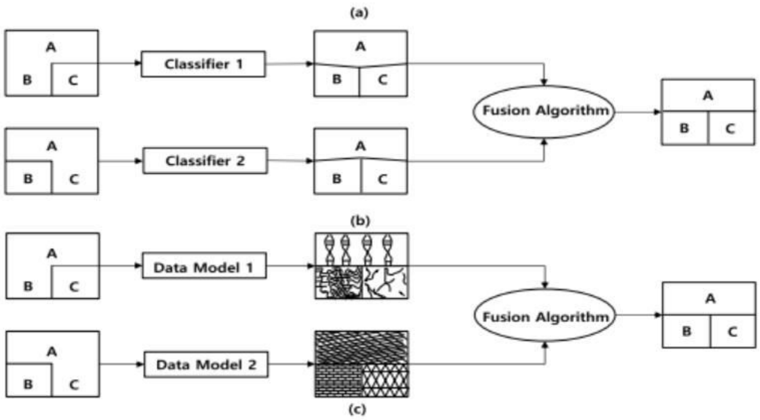


**Figure 3. Block diagram of data fusion model**ing (DIn et al., 2017)

## 2.3 Brooks-Iyengar Algorithm

This algorithm is proposed to understand and describe multiple sensors to measure various aspects of the physical world. In addition, we will discuss a new technique of using the Brooks-Iyengar algorithm in designing a system that will decentralize the data source of the appropriate measurement and thereby ensure the integrity of transactions on the Blockchain in its implementation.

The following section highlights the application of the Brooks–Iyengar algorithm in combination with a multisensor environment when using Blockchain systems. The proposed procedure using the algorithm will provide a means to decentralize data sources. The Brooks-Iyengar algorithm for distributed control in the presence of noisy data combines Byzantine agreement with sensor fusion(Brooks & Iyengar, 1996), (Brooks & Iyengar, 1998), (Chen, Lam, & Fan, 2005). In implementing the Brooks-Iyengar algorithm, multiple sensors and sensor data are essential to provide a new technique. The Brooks-Iyengar algorithm decentralizes the data source, which is the value in block transactions if the data source is dominated by one or several groups.

## 2.4 Multimodal Deep Learning Fusion

This model was designed by Diamantidou (2019), presenting a new multimodal Deep Learning methodology for filtering and combining data from various unimodal approaches used to detect UAVs. In particular, this study aimed to detect and classify potentially hazardous UAVs based on the fusion procedure (combining) the features of UAV detection provided by the unimodal component(Diamantidou, Lalas, Votis, & Tzovaras, 2019).

The concept used in this paper is an implementation of the Multilayer Perceptron architecture, which is combined with multimodal deep learning fusion. The fusion algorithm has three input streams: infrared stream, optro stream, and 2D radar stream. The extracted feature of the neural network in unimodal is a high representation of the raw input data to the neural network. At the same time, the implementation is based on the Perceptron Multilayer architecture. The Perceptron Multilayer algorithm consists of a merging layer and three fully connected layers (solid layer).

Figure 4 illustrates the proposed architectural concept and design of the data fusion framework. The neural network architecture has been designed with three input streams: thermal image stream (infrared), visual image stream (optro), and 2D radar stream. The implementation of the proposed methodology involves a merged layer to combine the three input streams mentioned above. Each stream is a different input tensor. The output of the concatenation layer returns a tensor containing the concatenation of all inputs. Utilizing the merged layer makes it easy to manipulate multiple input tensors because the unimodal input features are not closely related.

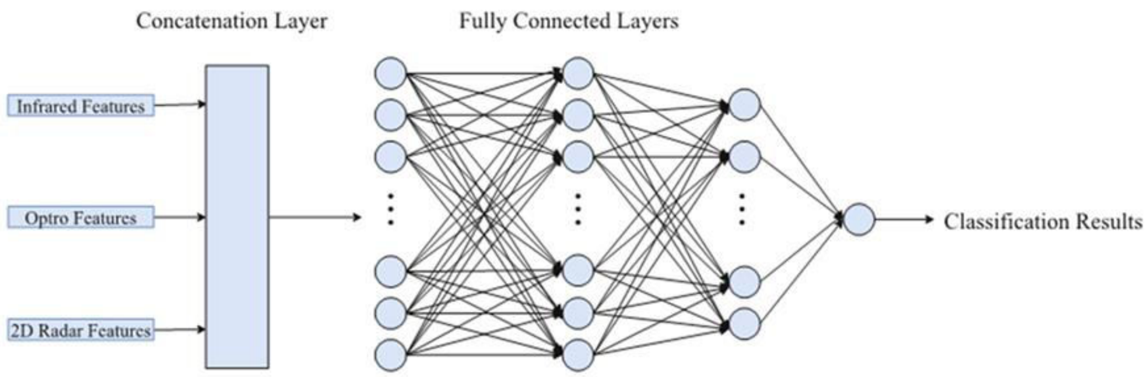


**Figure 4. Multilayer Perceptron architecture for deep learning fusion frameworks**(Diamantidou et al., 2019)**.**

## 3 Results and Discussion

From the four algorithms that have been described previously, we will discuss how to implement these algorithms into the c-UAV system. In addition, each performance resulting from combining multisensor data based on these algorithms will also compare each performance to achieve an optimal and efficient algorithm.

In a study using a combined algorithm of Kalman filter and Multi-Layer Perceptron, the problem of multisensor data fusion is applied to linear systems(Safari et al., 2014). The highest sampling rate is uniform, but the lower sampling rate is different and asynchronous. Each sensor system observes the state independently. Assuming that the state dynamics at the highest sampling rate are known and that the sampling rate ratio between sensor systems is a positive integer, a single-level approximation model for the original design is developed. A parallel Kalman filter is used for state estimation at each sampling rate, and a neural network is used for integrating state estimates.

The simulation results show better performance than previously published methods based on combined Kalman filtering due to a neural network-based sensor fusion approach. Future work may include extending the proposed algorithm to cases where the sampling rate ratio is a non-integer, the sampling rate ratio varies stochastically, or the highest sampling rate ratio is not uniform. Other future work could include the use of nonlinear networks and neural networks for data fusion from multiple Kalman filter outputs (e.g., fuzzy systems). This algorithm cannot be applied with sensor inputs with different features and dimensions because it causes many misperceptions of sensor data obtained. The proposed algorithm uses Enhanced MapReduce considering that the proposed algorithm is more efficient than a simple Java iteration implementation, as shown in Figure 5.

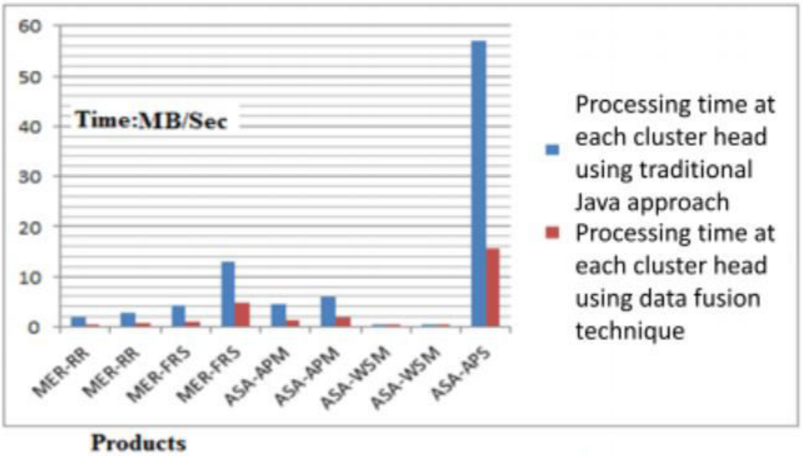


**Figure 5. Processing time is taken from various products**(Safari et al., 2014)**.**

This paper describes the transaction protocol, consensus algorithm, and proof of the work-based consensus algorithm of a standard blockchain. The Brooks-Iyengar algorithm decentralizes the data source of the appropriate measurement and thereby ensures the integrity of transactions on the Blockchain (Iyengar, Ramani, & Ao, 2019). However, standard blockchains with only one sensor in IoT or Smart Grids cannot decentralize data sources, thus making transaction values on Blockchain controlled by centralized nodes.

And most recently, a multimodal deep learning algorithm has been implemented to detect and identify the presence of UAVs in a protected area. Various experiments have been carried out to evaluate the proposed method(Gao, Zhong, & Li, 2011). By examining the results, it is observed that the Multilayer Perceptron algorithm has great potential to study the relationships and differences between the input data and achieve high classification results in UAV detection problems. The main achievement of the proposed approach is that this method successfully increases confidence inaccuracy while data from different modalities are combined. The results of fusion detection are compared with the unimodal detection of each modality to assess the performance of the fusion model. Figure 6[a–c] presents the results of UAV detection in the form of prediction probabilities based on unimodal features. In addition,

Figure 6[d] offers the results of UAV detection derived from the fusion model. As Figure 6[d] shows, a much better detection result was observed than Figure 6[a-c]. Improvements were noticed in detection accuracy when combined all three modalities were into the fusion model.

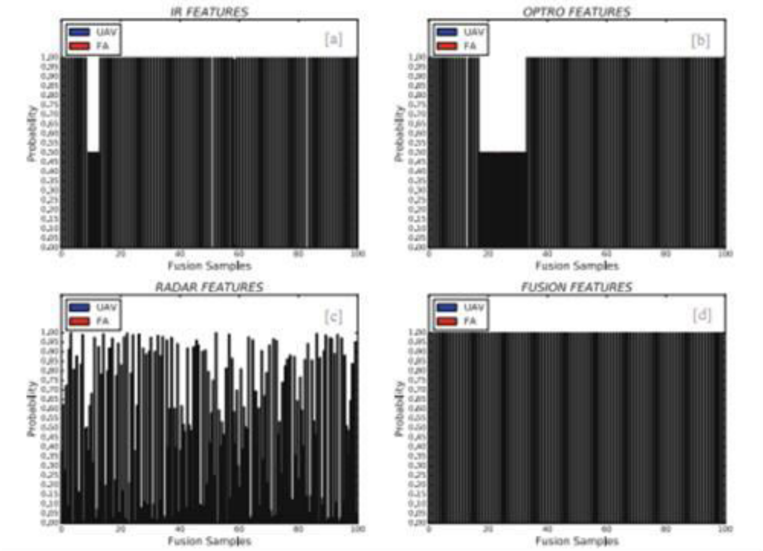


**Figure 6. Possible predictions as a result of the unimodal features evaluation procedure assessed three modalities for different feature types, namely: [a] infrared feature, [b] optro feature, and [c] 2D radar feature. [d] Predictive results in fusion models including unimodal features of infra-red, optro, and 2D radar modalities. X-axis: number of instant test samples. Y-axis: predicted value in terms of probability**(Diamantidou et al., 2019)**.**

For quality estimation purposes, two metrics that are more important than classification accuracy have been used. Precision and recall are both essential model evaluation metrics(Buckland & Gey, 1994). Precision is defined as the number of True Positives (TP) over the number of True Positives (TP) plus the number of False Positives (FP). In addition, recall is defined as the number of True Positives (TP) over the number of True Positives (TP) plus the number of False Negatives (FN). F1-Score is the average of precision and recall harmonics. There is no doubt that our approach seeks to maximize the F1-Score. This model has been evaluated in actual UAV flight capture.

## 4 Conclusions

The results of multi-sensor data fusion research based on several computational intelligence algorithms conclude that the most optimal algorithm used to detect various sensor features is Multimodal Deep Learning Fusion, by combining the Multilayer Perceptron algorithm in the learning process and testing the sensor data. In the research carried out, a multimodal neural network framework has been introduced, which can efficiently perform UAV detection tasks based on multiple input features. The proposed model architecture is based on the robust

Multilayer Perceptron algorithm. In addition, it has also thoroughly assessed the model on two benchmark metrics, namely: prediction probability and evaluation quality metric. The fusion detection results have been compared with the unimodal detection results to extract the validated results. It has successfully demonstrated the effectiveness of multimodal data learning and precisely establishing the fusion model efficiently, which is suitable for UAV detection. The following research that the author will do in the future is to develop this multimodal deep learning algorithm to detect and identify the situational identification of UAVs.

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