An Efficient UAV-based Artificial Intelligence Framework for Real-Time Visual Tasks

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Abstract: Modern Unmanned Aerial Vehicles equipped with state of the art artificial intelligence (AI) technologies are opening to a wide plethora of novel and interesting applications. While this field received a strong impact from the recent AI breakthroughs, most of the provided solutions either entirely rely on commercial software or provide a weak integration interface which denies the development of additional techniques. This leads us to propose a novel and efficient framework for the UAV-AI joint technology. Intelligent UAV systems encounter complex challenges to be tackled without human control. One of these complex challenges is to be able to carry out computer vision tasks in real-time use cases. In this paper we focus on this challenge and introduce a multi-layer AI (MLAI) framework to allow easy integration of ad-hoc visual-based AI applications. To show its features and its advantages, we implemented and evaluated different modern visual-based deep learning models for object detection, target tracking and target handover.

1 Introduction

Unmanned Aerial Vehicles (UAVs) have great potential to be widely used in real-life applications. Because of their low cost, safety benefit, and mobility, UAVs can potentially replace manned aerial vehicles in many tasks as well as perform very well in tasks that tradition manned aerial vehicles do not. This is especially true when UAVs are equipped with modern state-of-the-art AI technologies delivering astonishing performance in many challenging tasks (e.g., computer vision [9], natural language processing [10], etc.) Within this setting, despite the recent efforts, modern AI implementations are still missing due to the difficulties of real-time exchanging and control of the data shared between the UAV and the intelligent part of the system. This generally deny an easy development of ad-hoc AI solutions.

We propose an efficient and flexible multi layer AI (MLAI) framework which has been conceived considering the entire AI pipeline from sensor data reading to results delivery. We borrowed the long term software development technologies such as the quite common front-end and back-end methodology for our AI framework. For the front-end layer, a desktop user interface is implemented with the help of the object oriented C# and XAML technologies. For the middle communication layer, we setup a smooth socket message exchange to let a rapid communication between other layers. For the back-end layer, the python 3.x platform is adopted and frameworks such as pytorch, numpy, and opencv-python are exploited for AI. To control the UAV flight, we implemented an Android application using the commercial DJI SDK. To demonstrate the benefits of the proposed MLAI framework, we have selected the visual re-identification task [1]. This requires completion of the visual object detection, tracking and handover sub-tasks to be successfully completed. We have considered the recent breakthrough of deep neural networks (DNN) to tackle such tasks.

The major feature DNNs is the ability to learn visual features automatically. This contrasts with the feature-engineering approach where previous domain knowledge is required to come up with a suitable feature representation. Local receptive fields, shared weights, pooling, and sub sampling are the main concepts within traditional convolutional neural networks (CNNs). These help to handle target translations, scale variations, or distortions. In industry, the system needs to employ state-of-the-art technologies to meet customer requirements [11]. For this research, we implemented two top state-of-the-art AI algorithms as YOLOv3 [2] and DCFNet [3] to detect and track objects from UAV, respectively. YOLOv3 is one of the best algorithms for real-time object detection. Three versions have already been developed with significant continuous improvements. YOLOv3 is the latest version, which we implemented in this research. This algorithm is 1.5× or 2× faster than other solutions such as ResNet-101 [4] or ResNet-152 [4]. For visual object tracking, current state-of-the-art algorithms are founded on the Discriminative Correlation Filter (DCF) technique. Such a technique gives optimal real-time performance when multi-channel features can be exploited. It is a matter of fact that better features always increase tracking performance. Today the trend within this research topic is to use the multi-layer deep features for DCF tracking to improve the tracking performances. Among such methods, DCFNet [3] is a very light weight method achieving state-of-the-art performance. Due to this reason, it has been selected and implemented for real-time visual object tracking.

To finally, to conclude the re-identification, we implemented a new two-way handover approach which grounds on the previous work done in [1]. Concretely, the key contributions of the proposed work are:

- A novel and efficient architecture for visual-based AI system.
- Real-time state-of-the-art deep learning implementations.
- A two-way handover technique.
- Definition of minimal internet of drone things.

Systematic experiments conducted on real-world data have shown that the proposed solution:

- is able to detect multiple objects with a processing speed of 19.65 frames per second (fps).
- can track an object of interest in real-time (at 29.94 fps).
- is able to improve the one-way handover performance by a significant margin (about 30% accuracy improvement).

The rest of the paper is organized as follows. The proposed MLAI framework is described in Section 2. The internet of drone things is explained in Section 2.5. The details about the implemented deep learning algorithms and the handover process are discussed in Section 2.6 and 2.7, respectively. The experimental results are presented in Section 3. Finally, Section 4 provides the conclusions and future work.

2 The MLAI Framework

In the followin, we present the details of the proposed MLAI framework for drone-related AI applications. The overall framework pipelines is shown in Figure 1. The framework architecture has four layers which have been inspired from the long term web application development, hence considering a front- and back-end solution. The first layer is for front-end development, while the middle layer is in
charge of managing the communication between the front-end and back-end layers. The third layer consists of the drone flight controlling activities, while the fourth one is the back-end layer which is in charge of carrying out the AI activities. This is achieved by designing deep learning models through pytorch, numpy, opencv-python and additional utility libraries. The framework has the following main advantages:

- Portable. The front-end and the back-end layers might reside in different locations and places within the network environment.
- Feasible. Since AI frameworks are mostly developed through the usage of python platforms such that PyTorch [7], Tensor-Flow [8], and python itself, we don’t need develop another framework to use in different programming language.
- Multiple user interfaces. If additional user interfaces are needed (e.g., a user interface running on a mobile application), just adding a new simple socket connection is enough.
- Agile development and testing. Front-end and back-end developers can make suitable changes without worrying about dependencies, thus working independently and in parallel.

It is worth to note that, while it has been primarily designed for drone systems, the proposed MLAI framework can been seen as a general architecture for any AI implementations where real-time and easy exchange of data between a sensor and the intelligent part of the system is needed.

2.1 Front-end UI layer

The front-end layer consists of main user interface (UI) which has three sub components: (i) the real-time video panel, (ii) the map panel, (iii) and the user control panel. It is a desktop application designed following the model-view-controller pattern and implemented by using the XAML, C#, GMap.NET, and OpenCVSharp framework technologies. The main user interface is shown in Figure 2. The top video streaming panel shows the video footages acquired from the flying sensor, and adds any inference result that is delivered by the back-end AI layer through the middle communication socket layer. The left bottom map panel shows the UAV current position and has been implemented by using the GMap.Net component. The bottom right control panel shows the current status of the UAV by listing the vehicle model, latitude, longitude, altitude, ground speed, heading, camera tilt, and state information. Start and stop computer vision task control button as well as UAV automatic take off and stop control buttons are also present.

2.2 Middle communication layer

Here we discuss in detail more about socket handlers and how we can efficiently design the middle connection layer. We develop in this layer socket servers and clients which are handling video signal from front-end to back-end layer, exchange the messages as inference results, text messages, and commands. The important solution is to transfer the real-time video signal without latency and packet loss. Since UDP socket is the promising to have low latency however no nature for packet loss, we use TCP socket directly to smoothly handle the video signal without latency and packet loss. We develop algorithm to encode and decode the matrix of video frame. The algorithm is to perform the encoding matrix of video signal. With utility of OpenCV ImEncode function it takes the frame as input then encodes to bytes to transfer through socket to back-end AI layer.

In Algorithm 2, we use numpy library and opencv python since our AI models are working in python platform. To decode the frames, first, encoded matrix is converted into array then we applied opencv imdecode function to decode the matrix.
Algorithm 2: Matrix Decode

1: import cv2
2: import numpy as np
3: data = socket.recv(BUFFER_SIZE)
4: array = np.fromstring(data,np.uint8)
5: frame = cv2.imdecode(array, cv2.IMREAD_COLOR)

2.3 Back-end AI layer

In this section, we develop python platform with utilities from numpy, opencv-python, and PyTorch frameworks as shown in Figure 3. Main AI approaches are state-of-the-art algorithms as YOLO and DCFNet approaches. All state-of-the-art deep learning algorithms discussed in Section 2.6. It receives the video signal through socket from front-end layer and then once decodes the signal it does input that signal into AI models in well order. For real-time system, since our AI algorithms work in low resolution frame, it is always better to reduce the size of video frame. It receives all signals from front-end layer as video signal and object detect, track, and vision task stop command strings through communication middle socket layer. Then it sends back the information of object detection and tracking bounding box, recognized object labels, accuracy, and executing command result strings. To debug AI tasks we use two visual windows for object recognition and tracking algorithms as shown in Figure 3. Once front-end desktop application starts, we then run the back-end python platform up as well using shell calling API in C# technology.
To exchange data through connection, we mostly use low level things. The rest of whole setup and more details are given in Section as the minimum number of connected devices to have the AI and programmable drone industry availability, it is the optimal solution. In generally for standard case like today’s most distributed connections. It is mainly composed of 3x3 and 1x1 convolutional layers. The goal of the detection task is to predict the width and height as well as as the location of a bounding box enclosing an object of interest. In YOLOv3, these are the coordinates $t_x, t_y, t_w, t_h$.

In the following are the width and height of bounding box predictions correspond to:

$$b_x = \sigma(t_x) + c_x, b_y = \sigma(t_y) + c_y, b_w = pw + tw, b_h = ph + th$$ (1)

Let $\hat{t}_s$ be the ground truth for some coordinate prediction and $\hat{t}_s$ be the predicted value, then the gradient can be computed as $\hat{t}_s - t_s$. We can compute the by inverting the above equations. The model uses logistic regression to predict the objectness score for each bounding box. It predicts the classes of the bounding box which may contain multiple labels. Since the softmax has been shown to be not much relevant for good performance, it has not been included within the model. Hence, independent logistic regression classifiers have been used. For class predictions, the binary cross-entropy is used.

2.6 Deep Neural Networks for Drone

We implemented two strong deep neural network models for our UAV to track and recognize the objects. Both tracking and detection approaches are given in detail based original researches in [2], [3].

2.6.1 Target Detection and Recognition: An artificial neural network architecture is used to perform the feature extraction. Specifically, the adopted network follows a hybrid model inheriting from YOLOv2 [3], Darknet-19 and the modern residual networks. The network has 53 convolutional layers with some shortcut connections. It is mainly composed of 3x3 and 1x1 convolutional layers. The model uses logistic regression to predict the objectness score for each bounding box. It predicts the classes of the bounding box which may contain multiple labels. Since the softmax has been shown to be not much relevant for good performance, it has not been included within the model. Hence, independent logistic regression classifiers have been used. For class predictions, the binary cross-entropy is implemented.

2.6.2 Target Tracking: For DCFNet tracking approach, the conv1 from VGG [8] is only the convolutional layers for the lightweight network with 75KB. The output is forced to 32 channels and all pooling layers are removed. Stochastic Gradient Descent (SGD) algorithm is applied to train the network with momentum 0.9, weight decay and the learning rate. Twenty epoch is looped for the model with mini-batch size of 16. The online learning rate is fixed as 0.008 for the hyper-parameter in the correlation filter layer. We fixed the Gaussian spatial bandwith as 0.1 and the regularization coefficient as 1e-4. The patch pyramid is used with the scale factors.

2.7 Re-Identification (ReID) Handover Process

2.7.1 Two-Way Re-Identification: The proposed ReID scheme is shown in Figure 4. The whole process starts with a camera/UAV tracking the target of interest. We will refer to such a camera/UAV as the tracking sensor. During the tracking procedure the tracking sensor acquires images of the target (under different illumination conditions and poses) and computes the ReID features which are stored, together with the target ID, within the tracking sensor gallery. The assistant cameras/UAVs (dubbed assistant sensors) which are

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**Fig. 5:** Minimal Internet of Drone Things setup. All connection types are visualized from (1) to (4).

**Fig. 6:** Two-way Re-Identification pipeline. The current tracking object is surrounded by a red bounding box. Objects detected by each assistant sensor are depicted in magenta.

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**Algorithm 3: UAV Auto Heading**

1. Lat1.lng a;
2. Lat1.lng b;
3. //Calculate bearing
4. double lng1,lng2,lat1,lat2,
5. lngDiff,x,y,bearing;
6. lng1 = a.longitude;
7. lng2 = b.longitude;
8. lat1 = Math.toRadians(a.latitude);
9. lat2 = Math.toRadians(b.latitude);
10. lngDiff= Math.toRadians(lng2-lng1);
11. y= Math.sin(lngDiff)*Math.cos(lat2);
12. x=Math.cos(lat1)
13. *Math.sin(lat2)-Math.sin(lat1)
14. *Math.cos(lat2)*Math.cos(lngDiff);
15. bearing = (Math.toDegrees(16. Math.atan2(y, x)) +360)
16. bearing == 0
17. if bearing == 0 then
18. return 0;
19. return angle%180;
20. if d%2 == 0 then
21. end if
22. int d = bearing/180;
23. if d%2 == 0 then
24. return angle%180;
25. end if
26. int signum = Math.abs(angle)/angle;
27. int translatedAngle = angle%180 - signum*180;
28. return translatedAngle;
asked to support the current tracking sensor will receive the current tracking target feature representation. After this is received, they run the proposed detection and centroid tracking solutions one after the other. This is necessary to assign the same ID (within each assistant sensor list) to the objects that are appearing in their field-of-view (FoV) at different time instants. For each of such objects, the feature representation is computed and added to the gallery list of objects belonging the assistant sensor. After such an inclusion, the received target feature representation \( x \) is compared with the feature representation \( y \) of each image in the gallery list of the assistant by using the cosine similarity

\[
\cos(x, y) = \frac{x^T y}{||x|| ||y||} \tag{2}
\]

which returns a matching score representing the ReID confidence. If the match is above a threshold (currently set to 60% chance of matching) the features obtained from the new objects are sent back to the tracking sensor. This runs the second ReID match by using the feature representation received from the assistant sensor as the new probe. This is matched against the gallery list of objects belonging to the tracking sensor, which includes the current tracking object. The same cosine similarity is used as the matching metric. After the match with all gallery objects is concluded, a ranking list of candidates is obtained by sorting the matched gallery objects in descending order. We then count how many times the tracking target falls in the top-k matches of such a ranked list (we currently set \( k = 20 \)). We use such a counter \( z \) together with the number of times a specific object is received from the assistant drone \( t \) to weight the matching score as

\[
\phi(x, y, z, t) = z \cos(x, y) = z t \frac{x^T y}{||x|| ||y||} \tag{3}
\]

Such a score is finally sent back to the core system which is in charge of deciding to which assistant sensor the tracking sensor has to handover. This process is repeated until the tracking sensor receives the stop ReID signal and the selected assistant sensor receives the start tracking command. This completes the handover.

### 2.7.2 Target Feature Representation

To have a more robust solution to illumination changes and pose variations, in this last milestone, we have also introduced a new target representation (shown in Figure 7).

This leverages on the image pyramid framework to compute multi-level features for image stripes, which allow us to be more robust to left/right viewpoint changes and misaligned tracking results. We considered three pyramid levels with a split of the person into 3 different stripes at the first level. At the 2nd and 3rd levels of the pyramid, the target image is divided into 5 and 7 stripes, respectively. For each of the image stripes 4 different histograms are extracted from the Hue, Saturation, and \( a^* \) and \( b^* \) components of the Hue-Saturation-Value and CIEL\( a^* b^* \) color spaces. Histograms computed for all stripes are then concatenated to provide the final feature representation. Then obtained vector is finally normalized by using the power norm law followed by the L2 normalization.

### 3 Experimental Results

In this section, we discuss first about the setup, and then evaluate the efficiency of the MLAI framework, finally detection, tracking, and handover object ReID results are experimented in systematic scenarios.

#### 3.1 Setup

We setup the DJI Phantom 4, Matrice-100, their standard remote controllers, 2 Samsung Galaxy Note 4 mobile devices (CPU: Quad Core Snapdragon, 2.7GHz; RAM: 3GB), and 2 Asus Laptops (Republic of Gamers, CPU:Core i7-875H@2.20GHz, 2.21GHz, RAM:16GB, GPU: NVidia GeForce GTX 1070, 8 GB) as shown in Figure 8.

![Fig. 7: ReID feature description computation. Histogram feature extraction is carried out for each of the stripes dividing the target image at the different levels of the pyramid structure](image7)

**Fig. 7:** ReID feature description computation. Histogram feature extraction is carried out for each of the stripes dividing the target image at the different levels of the pyramid structure.

![Fig. 8: The setup with Phantom 4, it’s RC, Android device, and GPU powered laptop.](image8)

**Fig. 8:** The setup with Phantom 4, it’s RC, Android device, and GPU powered laptop.

#### 3.2 The MLAI Framework Efficiency

In this section, we evaluate the simple efficiency experimental results for the MLAI framework. The software performance index Apdex score is the industry standard for tracking relative performance of the software. Since our final product that using the MLAI is the software, Apdex works by specifying a goal for how long a specific request should take. In our case requests are mostly to detect and track that specific objects. Those requests are then classified into satisfied (fast enough), tolerating, not satisfied (too slow), and failed. The math formula is as:

\[
\text{Apdex Score} = \frac{C_s + \frac{C_t}{2}}{C_{total}} \tag{4}
\]

where \( C_s, C_t, C_{total} \) are satisfied count, tolerating count, total samples, respectively. In Table 1 we experimented 100 samples to request as track and detect the specific objects with threshold \( t = 0.5 \) sec and then according Apdex scores are computed.

| Request   | \( C_s \) | \( C_t \) | \( C_{total} \) | Apdex Score |
|-----------|----------|----------|----------------|-------------|
| Object Detect | 97       | 3        | 100            | 0.985       |
| Object Track   | 98       | 2        | 100            | 0.99        |
3.3 Detection and Recognition

To evaluate the performance of the selected YOLOv3 detector we have acquired footages from UAV camera. In the following sections we report on the performance achieved considering the Scenario 1 - person detection, Scenario 2 - vehicle detection, and Scenario 3 - multi objects detection, respectively.

3.3.1 Scenario 1 - Person Detection: We experimented the results on the person detection case as shown in Figure 9. A person was walking on the testing area and we collected here some frame sequences from the video. As we can see the algorithm works in real-time and continuously detecting.

![Figure 9: Scenario 1 - Person Detection. The person is walking on demonstration site.](image)

3.3.2 Scenario 2 - Vehicle Detection: We experimented the results on the vehicle detection case as shown in Figure 10. The drone is following the vehicle on the test area and we collected here some frame sequences from the video. As we can see the algorithm works real-time and continuously detecting the vehicle.

![Figure 10: Scenario 2 - Vehicle Detection. The vehicle is running on demonstration site.](image)

3.3.3 Scenario 3 - Multiple Objects Detection: In Figure 11 the drone is following the vehicle and person on the testing area and we collected here some frame sequences from the video. As we can see the algorithm works real-time and continuously detecting the vehicle and person both.

3.4 Tracking

In this section, we experiment the tracking results. To evaluate the tracking solution, we have collected multiple videos at the test bed site. Specifically, we have acquired footages simulating the evaluations scenarios.

3.4.1 Scenario 1 - Person Tracking: We report on the achieved results on the person tracking case as shown in Figure 12. A person was walking on the testing area. Results show that real-time performance are achieved with stable tracking results.

3.4.2 Scenario 2 - Vehicle Tracking: In Figure 14 the drone is following the vehicle on the testing area and we collected here some frame sequences from the video. As we can see the algorithm works real-time and continuously tracking the vehicle.

3.4.3 Scenario 3 - Multi Target Tracking: We experimented the results on the multiple objects as vehicle and person tracking case as shown in Figure 15. The drone is following the vehicle and person on the testing area and we collected here some frame sequences from the video.

3.5 Re-identification

Here we experiment the re-identification results. To evaluate the re-identification solution, we have collected multiple videos at the test bed site. Specifically, we have acquired footages simulating the evaluations scenarios. Please note here our proposed two way ReID approach has about 30% higher accuracy than one way ReID approaches. We show the experimenting results in Figure 13.

4 Conclusion

We proposed the efficient and novel MLAI general framework and implemented it for UAV AI implementation. Modern state-of-the-art hybrid deep learning approaches implemented to recognize and track
to bring AI for UAV in real-time to provide the novel and complete approach for object re-identification. And then the re-identification handover process is introduced in this research especially for UAV. We defined minimal IoDT for UAV. All main important algorithms are directly provided in this research to develop the novel UAV system powered by AI.

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Fig. 11: Scenario 3 - Multiple Objects Detection. The person and vehicle are moving on testing site.

Fig. 12: Scenario 1 - Person Tracking

Fig. 13: Two-way ReID experimental results. The first result is one way ReID. Second result is two way ReID. Correct match has a tick on its bottom, wrong ones have a cross.

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Fig. 14: Scenario 2 - Vehicle Tracking. The vehicle is driving on test site with normal speed.

Fig. 15: Scenario 3 - Multi Targets Tracking. The person is selected to track in multiple different objects.