TEST Engineering & Management

January - February 2020
ISSN: 0193 - 4120 Page No. 3187 - 3194

A Technical Research on UAV for Object Detection

Merugu Suresh, Associate Dean, Research & Development Centre, CMR College of Engineering & Technology, Hyderabad, Telangana, India (Email: msuresh@cmrcet.org)
NidaFathima, Junior Research Fellow, Research & Development Centre, CMR College of Engineering & Technology, Hyderabad, Telangana, India. (Email: nidafatima127@gmail.com)

Article Info
Volume 82
Page Number: 3187 - 3194
Publication Issue:
January-February 2020

Article History

Article Received: *14 March 2019*
Revised: *27 May 2019*
Accepted: *16 October 2019*
Publication: *19 January 2020*

Abstract

According to a Forbes report published in 2018, US drone industry has witnessed a dramatic commercial growth from merely $40 million in 2012 to a billion in 2017 as documented in the study conducted by MCKinsey and Company in December 2017. It is estimated by MCKinsey that by 2026 the commercial drones will annually impact $31 billion to $46 billion on country's gross domestic product.

Drones have been widely adopted for data capturing that can be used in the fields of defense, agriculture, emergency response and disaster management, conservation of endangered species, healthcare etc. For most of the applications of UAV, Real-time object detection is extremely crucial. In the last few years, considering the growth of drone industry and the interest of around 300 companies who are making substantial investments of time and resources in drone many technologies have been emerged for making advancement in the field of UAV focusing on object detection and recognition for UAV.

This paper summarizes a number of object detection techniques proposed till date by researchers. It reports the characteristics and requirements of UAV from object detection viewpoint. The objective of our research is to understand different architectures that are capable of detecting objects from aerial images. The main goal of this survey is to create an insight of an architecture that is accurate, fast, robust and utilizes low computation power.

Keywords: *Convolutional Neural Network(CNN), Unmanned Aerial Vehicle (UAV), object detection and recognition.*

I. INTRODUCTION

An Unmanned Aerial Vehicle (UAV) is expected to be a fully autonomous and a self governing system. To achieve this objective it is crucial to equip drones with the features of auto-pilot and smart computer vision that can perform functions such as detection, classification and tracking on its own. Therefore, it can be stated that one of the active area of research in the field of UAV is Object detection.

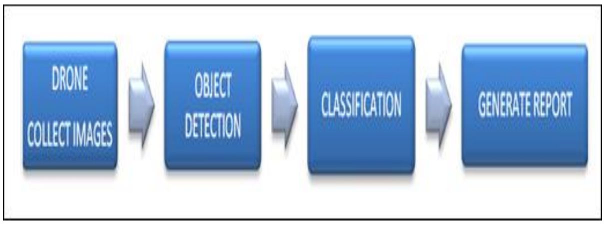

Figure 1. Work flow of UAV

But there are many challenges associated with the difficulty in detecting the objects such as the high computation power required to accomplish the task, accuracy in depicting the objects when the UAV is in motion or when the objects are not static and the time required to extract knowledge from the raw data obtained from UAV's camera.

The authors [1, 2, 3, 4, 5] tries to depict a solution for the above problem by following different procedures to obtain a balance between accuracy and speed while detecting the objects in order to fulfill the varied applications of UAV.

II. UNMANNED AERIAL VEHICLE

Unmanned Aerial Vehicle (UAV) is a quadcopter with no pilot on board. There are variety of UAVs that varies in terms of cost, size and applications. The cost of UAV ranges from few thousand dollars to billion dollars. The aircraft weight ranges from less than a pound to more than 40000 pounds.

TEST Engineering & Management
January - February 2020
ISSN: 0193 - 4120 Page No. 3187 - 3194

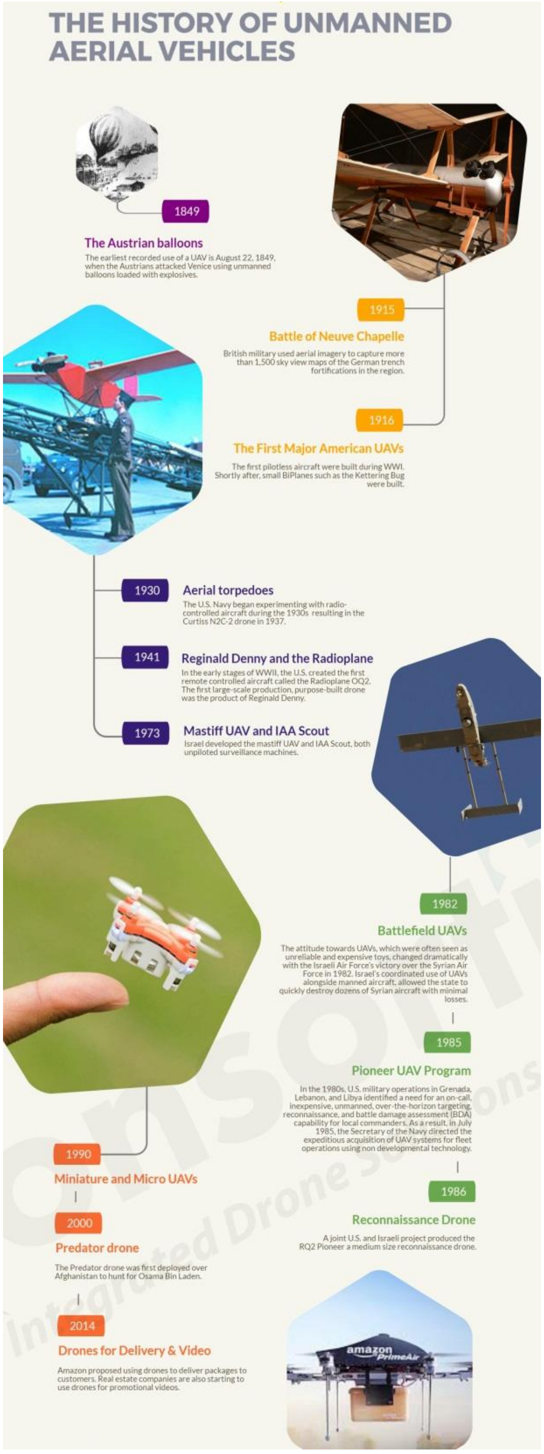

Figure 2. History of UAV [33]

A. Degree of Autonomy

UAV can be partially or fully autonomous i.e., some are flown by a pilot on the ground using a remote control to control the navigation of the aircraft and few other fly autonomously based on the preprogrammed flight plans. In both the systems there is no pilot on the board

B. Applications

In the modern world, UAV plays an important role and has influenced the society in multiple ways. Here is the list of field in which UAV is used extensively used

- Aeroscape – UAV are now used for maintenance of aircrafts
- Military – UAV is used for reconnaissance and attack in the battlefield
- Demining – UAV has the ability to quickly detect and clear mines
- Civil – UAV are found to be very useful in civil and commercial sector such as Archeology, cargo transport, conservation, healthcare, filmmaking, journalism, law enforcement, search and rescue, surveillance, agriculture etc.

C. Types

Considering its wide variety of applications different type of UAV have been created. They are

1. Research and development
2. Civil and Commercial UAV
3. Reconnaissance
4. Target and decoy
5. Combat
6. D. History

III. OBJECT DETECTION THROUGH CLOUD BASED CNN

Many applications of UAV require real time object detection. With the advancement in technology CNN has been discovered and is considered as the most prominent solution for solving the problem of object detection by recognizing image contents. Nevertheless, the computation demands in CNN are very high, requiring GPUs that overload the low weight drones.

A. Literature Survey

Convolutional Neural Network : The traditional multilayer, feed forward perceptron networks acts as base in understanding the concept of CNN, which is demonstrated as a powerful model that can accomplish tasks such as image segmentation, object detection and recognition [6,7,8]. CNN has the

January - February 2020
ISSN: 0193 - 4120 Page No. 3187 - 3194

ability to detect variety of objects in the images captured by the fast moving drones.

Cloud Robotics :

Cloud computing allows on demand availability and access to unlimited computer resources, that is especially used when large storage and high computation power is required. The key idea of cloud computing could be merged with robotics to explore the applications of Robotics by taking the benefit of the resources and services offered by clouds[9,10]

B. Challenges Met

It has been witnessed the technological advancements made are not up to par with the needs of the applications. The major reasons behind this discrepancy is object recognition algorithms, training data set requirements and extremely high computation power.

The author[1] tries to find a tradeoff between the detection capability of UAV and its computation demands, for doing so the author uses a hybrid approach. i.e., To reduce the computation requirement in order to not to overload the low weight drone author moves the computation to off board to the cloud. It takes benefit of cloud's unlimited resources and performs target recognition on cloud by using RCNN algorithm that has the ability to detect variety of objects. As this approach suffers from communication latency, to balance this negative consequence it performs navigation and stability on the board (UAV).

Thus by moving computation off board and keeping navigation and stability control on board it is able to detect the objects accurately in less time by using low power consumption.

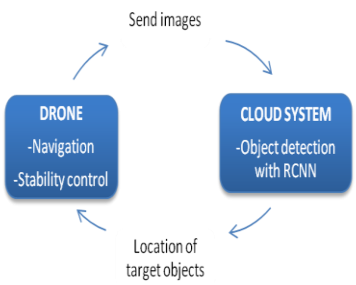

Figure 3. Object detection through Cloud based CNN

C. Future Insights

The object model evaluation can be parallelized among a set of machines so as to reduce the recognition time.

The training data set should have aerial images rather than consumer images to enhance the capability of the detector as the drones' takes images from aerial view.

Finally, Drone should have the ability to find its own location without using artificial pointers

IV. OBJECT DETECTION THROUGH AN EMBEBBED SYSTEM

Drone are used in variety of applications and it is necessary to equip drones with powerful cameras, smart computer vision and autopilot capabilities. In order to create a drone that has the capability to support the above mentioned necessities, many frameworks have been created that aims at creating an architecture that is accurate, robust and fast.

A. Literature Survey

Deep Neural Network: Computer vision tasks such as image classification, detection and segmentation can be deployed using the technique called 'Deep Neural Network'. Many advancements have been made in this field starting from 2012 till date by creating AlexNet, VGGNet, GoogleNet, ResNet and SqueezeNet[11,12,13,14,15] which greatly improved image recognition accuracy. Among these methods SqueezeNet is considered to be the most optimized that requires less computation and has higher accuracy.

Object detection using deep learning through Fast CNN, Faster CNN, SSD, YOLO detectors.

The various methods mentioned above are used for object detection and they have some advantages and disadvantages.

Mainly we focus on two key points for performing the comparison among these different techniques i.e., accuracy and speed.[16,17,18]

In terms of accuracy Faster RCNN out performs all the other techniques and in terms of speed YOLO out performs the other techniques.

January - February 2020
ISSN: 0193 - 4120 Page No. 3187 - 3194

SSD is considered to be the most stable method as it maintains a balance between speed and accuracy.

Figure 4. Comparison of detectors [34]

Trackers:

Here we intend to discuss and compare the popular techniques for tracking such as KCF and MDNet.

MDNet is a visual tracker based on CNN which requires high computation power and is relatively slow whereas KCF is a fast method requiring less computation and storage requirement.[19,20]

B. Challenges Met

Applications of drones require a technology that enables UAVs to automatically track and detect the environment. The author[2] builds a framework called “Deep Drone” that can be mounted onto the drone. It is an embedded system that has an ability to power drone with computer vision and autopilot. The system aims to balance the speed and accuracy by using a combination of techniques for detection and tracking.

The author uses Faster CNN for Detection which expensive to compute and it is slow but very accurate. KCF for Tracking which is inexpensive to compute and it is fast but less accurate.

In the system, tracking is performed very frequently whereas detection is performed only when the confidence of the tracker is below the level (threshold). Thus, it creates an architecture that is both accurate and fast.

C. Future Insights

- Advancement in the field of tracking algorithm is required as it has been witnessed that the video captured by the drone has to be continuous for KCF to perform correctly. If this requirement is not met it results in error.

- The tightness of the bounding box has a huge impact on the detection ability. If it is not tight, the boundary might incorporate irrelevant objects that might affect the result. Thus a better technique is required address this problem.

V. OBJECT DETECTION USING CNN YOLO DETECTOR

Fully autonomous UAV is in demand in modern society. To make UAV fully automated ability to take decision on its own play an important role. UAV should be able to perform Detection (object sighting) and Classification (comprehension) without human intervention.

A. Literature Survey

Deep learning: It is a way to implement neural network approach and it helps to teach machine to detect and classify object on its own.

Neural Network Algorithms:

It has the ability to perform real time parallel processing using GPUs that can handle multiple tasks at a time.[21,22,23]

B. Challenges Met

The author[3] uses CNN based software called YOLO that takes raw data as input and it has the ability to detect and classify objects from it.

The working process is divided into three main steps

1. Flying drones capture data

2. Onboard system that detect and classify objects (YOLO)

3. Decision making based on the information obtained from 2nd step

The proposed architecture has many advantages such as there is a significant increase the accuracy of detection and drastic reduction in memory constraints as the algorithm uses same filters on each pixel and a huge fall in the computation time as

January - February 2020
ISSN: 0193 - 4120 Page No. 3187 - 3194

it performs tasks parallel.

Thus the architecture improves the performance on the whole.

C. Future Insights

CNN results in high computation power that sometimes overloads the UAVs.

Even if YOLO is been used to perform object detection and classification, CNN has to be trained with correct parameters.

The accuracy and reliability of CNN depends solely on the parameters, therefore some measures have to be taken to estimate the parameters properly.

VI. OBJECT DETECTION USING CNN SSD DETECTOR

UAV are low cost and low weight systems. The source of power to perform task is limited and less than the needs of its application. When deploying a UAV the key points to focus is

- To use minimal power as it may inversely effect the battery life and flight time of UAV
- To make critical decisions process the data with low latency.

A. Literature Survey

CNN detectors : CNN detectors can be classified into two categories. They are

- Region based detectors – Faster RCNN is a prominent example[24]
- Single shot detectors – YOLO is a prominent example

These detectors and there comparisons have been discussed above.[17]

B. Challenges Met

Traditional approaches either perform computation on board or on cloud. If computation is performed on system it requires high power and if it is performed on cloud it will suffer from latency. In order to find a solution to above mentioned problem the author[4] aims to reduce both computation cost and latency by employing a technique that is optimized to run on embedded platform on UAV.

SSD detector is a single shot detector aims to combine the performance of YOLO with the accuracy of Faster CNN. Thus increases the accuracy of detection by multiple scales.

C. Future Insights

By applying finer level optimization in order to reduce the bitwidth precision the performance can further be improvised.

To enhance the accuracy in detection the system should be trained with aerial images.

VII. OBJECT DETECTION USING SVM CLASSIFIER& RESULTS

UAV have become capable to capturing high resolution remote sensing images. These images encompasses huge amount of spatial and contextual information and they are often found to be useful in many applications of UAV such as vegetation monitoring, mapping archeological sites, traffic management etc.[25,26,27]

Literature Survey

Car detection and counting has also gained a lot of importance in the recent years, as it is essential for traffic management and urban planning.[28,29,30] There are many techniques proposed to accurately estimate the car count in certain areas.

Shadow exploiting and Bayesian network was one of the earliest techniques for car detection followed by using online boosting on Haar features and histogram[30,31]. The author [28,29] used a combination of SIFT and SVM to detect the cars accurately.

Using supervised sliding window search has been considered as state of art for car detection. However, it suffers from many drawbacks i.e., it is very time consuming process and may lead to erroneous result if bounding area is not chosen properly.

Challenges Met

With an aim to increase the detection rate and reduce the computation time author[5] proposes a

January - February 2020
ISSN: 0193 - 4120 Page No. 3187 - 3194

framework that uses segmentation techniques and deep learning approaches for detection of cars in a region and it is found to be better than all the previous techniques that were developed in this area.

The proposed method has four main steps

1. Using mean shift algorithm the high resolution image is segmented into regions that are later inspected for presence of car

2. Using pre trained CNN the feature extraction process is carried out on the window around the candidate region.

3. Using SVM classifier the regions are classified, it gives a binary map that segments the image into car and no car class.

4. Morphological operations and inspection is carried out on to fine tune the binary map to isolate cars in the region.

The main features of this method is it takes the advantage of Mean shift algorithm in order to reduce the search space and CNN with SVM to extract highly descriptive features. Thus, the proposed technique has been able to achieve high accuracy in less computation time.

Future Insights

Accuracy in the proposed method can further be improvised by focusing on removing the false positives, as the framework suffers from high FP rate and furthermore the car count accuracy can be improved if some technique is proposed that can detect each car separately.

VIII. CONCLUSION

Throughout the survey we have discussed many new technologies that have been proposed for UAV object detection. We hope that the description mentioned in challenges met section will provide the researchers with the base knowledge that is required to investigate and further propose some solutions for the opportunities mentioned in future scope section thereby improving UAV applications in the future.

IX. REFERENCES

[1] Lee, J., Wang, J., Crandall, D., Šabanović, S., & Fox, G. (2017, April). Real-time, cloud-based object detection for unmanned aerial vehicles. In 2017 First IEEE International Conference on Robotic Computing (IRC) (pp. 36-43). IEEE.

[2] Han, S., Shen, W., & Liu, Z. (2016). Deep Drone: object detection and tracking for smart drones on embedded system.

[3] Radovic, M., Adarkwa, O., & Wang, Q. (2017). Object recognition in aerial images using convolutional neural networks. Journal of Imaging, 3(2), 21

[4] Kyrkou, C., Plastiras, G., Theocharides, T., Venieris, S. I., &Bouganis, C. S. (2018, March). DroNet: Efficient convolutional neural network detector for real-time UAV applications. In 2018 Design, Automation & Test in Europe Conference & Exhibition (DATE) (pp. 967-972). IEEE

[5] Ammour, N., Alhichri, H., Bazi, Y., Benjdira, B., Alajlan, N., &Zuair, M. (2017). Deep learning approach for car detection in UAV imagery. Remote Sensing, 9(4), 312.

[6] Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 580-587).

[7] LeCun, Y., Bottou, L., Bengio, Y., &Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

[8] Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., & Darrell, T. (2015). Long-term recurrent convolutional networks for visual recognition and description. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2625-2634).

[9] Goldberg, K., & Kehoe, B. (2013). Cloud robotics and automation: A survey of related work. EECS Department, University of California, Berkeley, Tech. Rep. UCB/EECS-2013-5.

[10] Kehoe, B., Patil, S., Abbeel, P., & Goldberg, K. (2015). A survey of research on cloud robotics and automation. IEEE Transactions on

automation science and engineering, 12(2), 398-409.
[11] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
[12] Iandola, F. N., Han, S., Moskewicz, M. W., Ashraf, K., Dally, W. J., &Keutzer, K. (2016). SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and< 0.5 MB model size. arXiv preprint arXiv:1602.07360.
[13] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).
[14] Simonyan, K., &Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
[15] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ...&Rabinovich, A. (2015). Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9).
[16] Gkioxari, G., Girshick, R., & Malik, J. (2015). Contextual action recognition with r* cnn. In Proceedings of the IEEE international conference on computer vision (pp. 1080-1088).
[17] Redmon, J., Divvala, S., Girshick, R., &Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).
[18] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems (pp. 91-99).
[19] Henriques, J. F., Caseiro, R., Martins, P., & Batista, J. (2012, October). Exploiting the circulant structure of tracking-by-detection with kernels. In European conference on computer vision (pp. 702-715). Springer, Berlin, Heidelberg.
[20] Nam, H., & Han, B. (2016). Learning multi-domain convolutional neural networks for visual tracking. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4293-4302).
[21] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).
[22] Sermanet, P., Eigen, D., Zhang, X., Mathieu, M., Fergus, R., &LeCun, Y. (2013). Overfeat: Integrated recognition, localization and detection using convolutional networks. arXiv preprint arXiv:1312.6229.
[23] Donahue, J., Jia, Y., Vinyals, O., Hoffman, J., Zhang, N., Tzeng, E., & Darrell, T. (2014, January). Decaf: A deep convolutional activation feature for generic visual recognition. In International conference on machine learning (pp. 647-655).
[24] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems (pp. 91-99).
[25] Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. ISPRS Journal of photogrammetry and remote sensing, 92, 79-97.
[26] Berni, J. A., Zarco-Tejada, P. J., Suárez, L., &Fereres, E. (2009). Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle. IEEE Transactions on geoscience and Remote Sensing, 47(3), 722-738.
[27] Lin, A. Y. M., Novo, A., Har-Noy, S., Ricklin, N. D., &Stamatiou, K. (2011). Combining GeoEye-1 satellite remote sensing, UAV aerial imaging, and geophysical surveys in anomaly detection applied to archaeology. IEEE Journal of selected topics in applied earth observations and remote sensing, 4(4), 870-876
[28] Lin, A. Y. M., Novo, A., Har-Noy, S., Ricklin, N. D., &Stamatiou, K. (2011). Combining GeoEye-1 satellite remote sensing, UAV aerial imaging, and geophysical surveys in anomaly detection applied to archaeology. IEEE Journal of selected topics in applied earth observations and remote sensing, 4(4), 870-876.
[29] Moranduzzo, T., &Melgani, F. (2013). Automatic car counting method for unmanned

aerial vehicle images. IEEE Transactions on Geoscience and Remote Sensing, 52(3), 1635-1647.

[30] Moranduzzo, T., &Melgani, F. (2014). Detecting cars in UAV images with a catalog-based approach. IEEE Transactions on Geoscience and Remote Sensing, 52(10), 6356-6367.

[31] Ram, T. Z., Zhao, T., &Nevatia, R. (2001). Car detection in low resolution aerial images. In Image and Vision Computing.

[32] Kluckner, S., Pacher, G., Grabner, H., Bischof, H., & Bauer, J. (2007, October). A 3D teacher for car detection in aerial images. In 2007 IEEE 11th International Conference on Computer Vision (pp. 1-8). IEEE.

[33] Weblink: https://cv-tricks.com/object-detection/faster-r-cnn-yolo-ssd/amp/ For comparison of object detectors [05/2019, 16:39].

[34] Weblink: https://consortiq.com/media-centre/blog/short-history-unmanned-aerial-vehicles-uavs History of UAV