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Drone types and its applications - A survey

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Abstract - *Abstract—Drones are a popular device with its application in several areas like surveillance and security, agriculture, mapping, construction and infrastructure inspection, data collection, search and rescue, logistics and package delivery. Drones mounted with camera are popularly used for surveillance today, in situations like COVID-19. In today's world due to the availability of large amount of data in the form of images and videos, it is very difficult to recognize and perceive this huge amount of information manually and it is very important to analyze this data and perform operations on it. Moreover, performing such activities for drone captured videos and images is still a challenging task. This task involves difficulties like low quality images, pose variations, occlusion and non-availability of annotated data set. With the advent of technologies like artificial intelligence and computer vision the task becomes easy. There is a vast amount of research performed in this area. This work focuses to present a detailed literature survey of drone types, applications and activity detection work done on drone captured videos/images*

Key Words: Drone, UAV

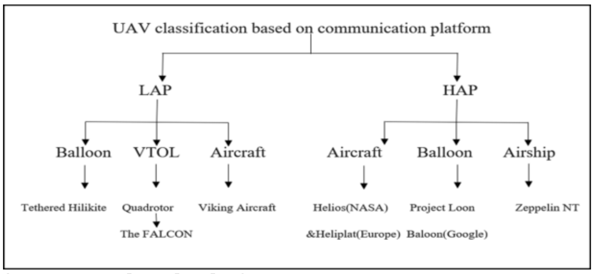
1.INTRODUCTION

Unmanned aerial vehicle drones equipped with cameras have been deployed in many applications to support public safety, military, transport systems for surveillance, delivery, search and rescue [1],[2],[3]. Automatic understanding of visual data collected from these platforms become highly demanding which brings computer vision, pattern recognition and machine learning much closer to drone technology to solve problems related to object detection [4,5], object tracking [4,6] and activity detection [7]. Object is any entity in a video, detected based on the context. Tracking the object drives temporal (feature) as an attribute in understanding the behavior, spatial geometry and local geometry of the object based on the context. Cumulatively analyzing the object detection and tracking over time in a video, labels the activity in context to scenario. An "Activity" (e.g., interaction between people) can be defined as a series or composition of actions where "Actions" are atomic motion patterns, often gesture-like, single clear-cut trajectory, single nameable behavior (e.g., sit, wave arms).

Many works have been reported in literature on computer vision algorithms, pattern generation and recognition methodologies with intelligent machine learning techniques but they are not optimal for deployment into drone-based applications due to various challenges such as view point changes, scales, lighting effects , contextual data generated on random requirements , design of drones with camera specifications , significant object appearance changes, variant illumination , occlusion, blur motion, rapid pose variation, cluttered background environments, and onboard mechanical vibrations.

2. DRONE TYPES

Drones can be classified based on weight, size, flight range, altitude and communication platform as follows: [8]



*** LAP: Low Altitude Platform**

*** HAP: High Altitude Platform**

***VTOL-Vertical take-off and landing**

LAP operates at an altitude of less than 10 km whereas HAP operates at an altitude of above 10Km

Fig- 1: Drone Categorization based on communication platform

Figure 1,2,3 and 4 gives a clear illustration of various types of drones available and their classification based on weight, size, flight range, altitude and communication platform. From air surveillance and artistic shoots, to the inspection of industrial facilities and mapping, drones have a wide prospect of applications. Choosing a drone for any of these applications should be done carefully depending on the requirement.

III.APPLICATION OF DRONE

Due to its ability to cover larger area and reach places which are physically difficult for a human and with the advent of technology, drones are being used for different applications like data collection [9], search and rescue [15], mapping [10], construction and infrastructure inspection [12], logistics and package delivery [12], agriculture [13], surveillance [14].

Data Collection and Observation:

The most common use of UAVs in humanitarian response today is data-collection and observation. UAVs can be equipped with a wide range of monitoring equipment, from a strapped-on smartphone to infrared systems or Synthetic Aperture Radar (SAR) that can see through cloud cover, forest canopy or even buildings. The analysis of data from these devices ranges from straight-forward to quite technically complex.[9]

The proposed drones' categorization by Zakora and Molodchik based on their weight and flight range

Designation	Weight range	Flight range
Micro and mini UAVs close range	W≤5kg	25km≤R≤40km
Lightweight UAVs small range	5kg<W≤50kg	10km≤R≤70km
Lightweights UAVs medium range	50kg<W≤100kg	70km≤R≤250km
Average UAVs	100kg<W≤300kg	150km≤R≤1000km
Medium heavy UAVs	300kg<W≤500kg	70km≤R≤300km
Heavy medium range UAVs	1500kg≤W	70km≤R≤300km
Heavy UAVs large endurance	1500kg≤W	R≤1500km
Unmanned combat aircraft	500kg≤W	R≤1500km

Fig- 2: Categorization of Drone based on weight and flight range

In November 2013, Super Typhoon Haiyan devastated the city of Tacloban in the Philippines. Several private sector firms and NetHope, a consortium of NGOs used UAV, with a range of up to 5 kms and a high-resolution video camera, to assist humanitarian. The UAV was used first to identify where to set up a base of operations,12 and then to check if roads were passable, a task that could take days when done on foot or by helicopter. The UAV was also flown up the coast to evaluate damage from storm surge and flooding and to see which villages had been affected. The aerial assessments helped to speed up the efforts, cut down on wasted time and work, and make them more accurate in their targeting of assistance. It was also suggested that the UAV might have located survivors in the rubble using infrared cameras if it had arrived within 72 hours. [9]

Drone Categorization based on their weight

➤ By Brooke-Holland :

Class	Type	Weight range
Class I(a)	Nano drones	W≤200g
Class I(b)	Micro drones	200g<W≤2kg
Class I(c)	Mini drones	2kg<W≤20kg
Class I(d)	Small drones	20kg<W≤150kg
Class II	Tactical drones	150kg<W≤600kg
Class III	MALE/HALE/Strike drones	W>600kg

➤ By Arjomandi et al.

Designation	Weight range
Super heavy	W>2000kg
Heavy	200kg<W≤2000kg
Medium	50kg<W≤200kg
Light	5kg<W≤50kg
Micro	W≤5kg

➤ By Weibel and Hansman

Designation	Weight range
Micro	W<2lbs
Mini	2lbs<W≤30lbs
Tactical	30lbs<W≤1000lbs
Medium and high altitude	1000lbs<W≤30,000lbs
Heavy	W>30,000lbs

Fig- 3: Categorization of Drone based on weight

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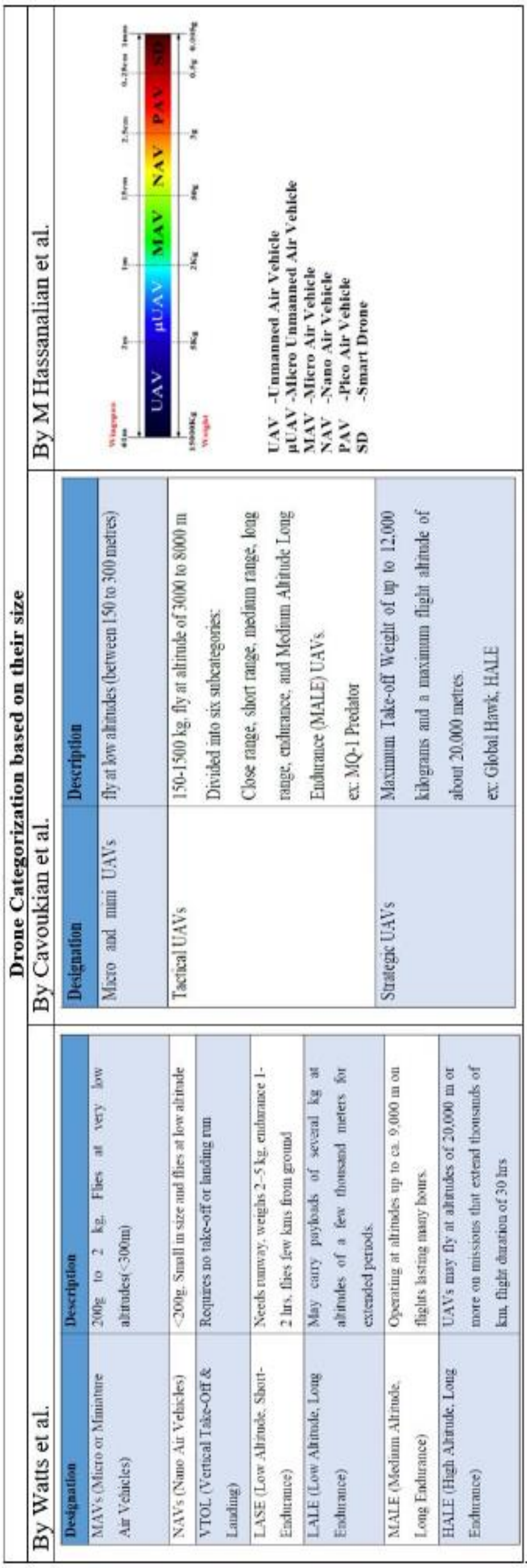

Drone Categorization based on their size

By Watts et al.

Designation	Description
MAVs (Micro or Miniature Air Vehicles)	200g to 2 kg. Flies at very low altitudes(<300m)
NAVs (Nano Air Vehicles)	<200g. Small in size and flies at low altitude
VTOL (Vertical Take-Off & Landing)	Requires no take-off or landing run
LASE (Low Altitude, Short-Endurance)	Needs runway, weighs 2–5 kg, endurance 1-2 hrs, flies few kms from ground
LALE (Low Altitude, Long Endurance)	May carry payloads of several kg at altitudes of a few thousand meters for extended periods.
MALE (Medium Altitude, Long Endurance)	Operating at altitudes up to ca. 9,000 m on flights lasting many hours.
HALE (High Altitude, Long Endurance)	UAVs may fly at altitudes of 20,000 m or more on missions that extend thousands of km, flight duration of 30 hrs

By Cavoukian et al.

Designation	Description
Micro and mini UAVs	fly at low altitudes (between 150 to 300 metres)
Tactical UAVs	150-1500 kg, fly at altitude of 3000 to 8000 m Divided into six subcategories: Close range, short range, medium range, long range, endurance, and Medium Altitude Long Endurance (MALE) UAVs. ex: MQ-1 Predator
Strategic UAVs	Maximum Take-off Weight of up to 12,000 kilograms and a maximum flight altitude of about 20,000 metres. ex: Global Hawk, HALE

By M Hassanalian et al.

UAV -Unmanned Air Vehicle
µUAV -Micro Unmanned Air Vehicle
MAV -Micro Air Vehicle
NAV -Nano Air Vehicle
PAV -Pico Air Vehicle
SD -Smart Drone

Fig- 4: Categorization of Drone based on their size

2.Search and Rescue:

UAVs equipped with infrared or other speciality cameras can be used search and rescue operations. For example, the European Union is funding ICARUS, a research project to develop unmanned search and rescue tools to assist human teams. [15]

In January 2019, 88-year-old Luis Reyna Zuniga was reported missing after leaving his home in Brownsville, Texas at 5:30 p.m. Search and rescue team members pooled their efforts with local police and fire department personnel, and deployed a drone with a thermal camera to try and find the missing man.

3. Mapping:

UAVs can rapidly produce geo-references (GPS accurate) or 3D maps that are often more detailed and faster than satellite imagery. [10]

Kathmandu university students along with drone and software experts obtained huge aerial maps using drones. The imagery along with local villagers' knowledge was used to locate safe sources of drinking water, dangerous debris, displaced people, ruined buildings and transportations networks Nepal Earthquake (2015). [11]

4. Construction and Infrastructure Inspection:

The net market value of the deployment of UAV in support of construction and infrastructure inspection applications is about 45% of the total UAV market. So there is a growing interest in UAV uses in large construction projects monitoring and power lines, gas pipelines and GSM towers infrastructure inspection.[12]

In 2016, it was reported that Pacific Gas and Electric Company (PG&E) performed drone tests to inspect its electric and gas services for better safety and reliability with the authorization from Federal Aviation Administration (FAA).The inspections focused on hard-to-reach areas to detect methane leaks across its 70,000-square-mile service area. In the future, PG&E plans to extend the drone tests for storm and disaster response. [12]

5.Logistics and package delivery:

UAVs can be used to transport food, packages and other goods. In health-care field, ambulance drones can deliver medicines, immunizations, and blood samples, into and out of unreachable places. They can rapidly transport medical instruments in the crucial few minutes after cardiac arrests. They can also include live video streaming services allowing paramedics to remotely observe and instruct on-scene individuals on how to use the medical instruments.

The US military uses unmanned Kaman K-Max helicopters that can deliver over 2,700 kg in Afghanistan,18 a few delivery projects have been tested in China, and pilot projects have been announced in Australia and New Zealand, by the US retailer Amazon,22 and others.[12]

6.Agriculture:

UAVs can be utilized in precision agriculture (PA) for crop management and monitoring, weed detection, irrigation scheduling, disease detection, pesticide spraying, and gathering data from ground sensors (moisture, soil properties, etc.,) [12]

A French farming cooperative, OCEALIA Group with 7,200 members and nearly 900 employees have been using drones to gain valuable fertilization data. The drone's data is used to measure the amount of dry matter in the field and nitrogen absorption at key stages of the crop's development. For farmers looking solely to increase yield, a flight takes place when the crop is between Z30 and Z33 stage, while for those looking to boost crop quality—i.e. increase the amount of protein in the plant—the flight instead takes place at Z39 stage. The OCEALIA farmers who have used our AIRINOV-supported drone service have recorded an average yield increase of 10%, compared to parcels analyzed using traditional, non-drone methods.[13]

7. Surveillance:

Drone can be used to gather information about specific targets, which might be individuals, groups or environments.

The Heron successfully monitored a drug smuggling ship off the Pacific coast of El Salvador in 2009. [14]

4. TYPES OF CAMERA MOUNTED ON DRONES:

A wide range of sensor applications are available to be mounted on drones. Even though drone with RGB cameras are common, their miniature and low-cost versions are available, such as multispectral, hyperspectral, short/mid-wave range cameras (e.g., thermal) and light-weight LiDAR (light detection and ranging). Knowing the characteristics of these sensors and their specifications will better inform engineers and scientists when for building surveillance applications.[16]

1. **RGB Cameras**: Modern drone mounted with RGB cameras are used for remote sensing applications.[18] As compared to other types of sensors, there exist a wide range of RGB cameras on the market, and for different applications, selecting appropriate RGB cameras mounted on a drone can be a key to success. Common parameters for selecting RGB cameras include camera lens, resolution and quality of the charge coupled device (CCD)/complementary metal oxide semiconductor (CMOS) chips (pixel size and noise level). High-quality cameras ensure good photogrammetric products and low-signal/noise-ratio data for data analysis. Normally, highly integrated drone-systems are easy to transport and operate, while the mountable RGB cameras are often confined to a few models allowing for seamless control. Sometimes, professional photogrammetric users favor customized/less integrated systems in order to be able to access a larger collection of RGB cameras for different applications. Many remote sensing applications largely rely on RGB camera-based products, such as analyses for tree crowns detection, vegetation growth monitoring and change analysis in a local scale.

Advantages: (1) high availability in products ranging across different levels of cost, resolution, and weight; (2) easy to be integrated in different platforms (3) well-modelled camera geometry with a large number of software solutions; and (4) videos. Disadvantages: (1) Often come without radiometric/geometric calibration; and (2) lack of spectral information for many tasks [16]

2.Light-Weight Multispectral Cameras:

Due of the benefits of obtaining spectral information in the red-edge and near-infrared band for vegetation applications in an extremely high resolution, multispectral cameras are one of the most commonly used sensors in addition to RGB cameras in the drone sensors family .Even though the RGB cameras are able to provide information related to the vegetation, the spectral sensitivity to the chlorophyll level of the vegetation is, however, limited for more sophistically analysis such as plant health quantification and disease detection. Near-infrared cameras can be used to derive vegetation indices (VIs) such as Normalized Difference Vegetation Index (NDVI) and others such as Green Normalized Difference Vegetation Index (GNDVI) and Enhanced Normalized Difference Vegetation Index (ENDVI). The multispectral cameras mounted on a drone may contain up to a few tenth of bands in addition to normal RGB bands. A great benefit for drone-based multispectral sensors is the yielded data with much higher resolution (better than 30 cm Ground Sampling Distance (GSD)) that are normally not attainable in traditional multispectral RS.

Advantages: (1) wider spectrum range and narrower bandwidth; (2) often come with means of radiometric calibration; (3) most of the sensors still follow a perspective model that can be well-processed for geometric reconstruction; and (4) allow for sub-decimeter multispectral mapping. Disadvantages: (1) data format compatibility (sometimes 12 or 16-bit) for software packages; (2) as a component of a drone, its cost remains to be relatively high; (3) sensor compatibility to drones may be limited; and (4) videos may not be available [16]

3. Light-Weight Hyperspectral Sensors

Hyperspectral cameras are often very capable while they are comparably less accessible due to their high cost and constraints in sensor compatibility to drones. In order to capture images with hundreds of narrow bands (5–10 nm bandwidth), most of the current light-weight hyperspectral sensors are linear-array cameras [19].

Advantages: abundant spectral information, 10 nm-level bandwidth for more advanced applications in material identification and so on. Disadvantages: (1) high cost; (2) most of them are linear-array and require specialized software, and the users may take care of the data format and geometric corrections; (3) dimension reduction is needed for typical classification tasks; (4) sensor compatibility to drones may be limited; and (5) videos may not be available [16]

4. Light-Weight Thermal Infrared Sensors

As one of the mid-infrared-range passive sensors (wavelength between 3 and 35 μm) , the thermal infrared sensors are broadly used in various surface temperature and thermal emission measurements. The resolution benefit of the UAV-borne sensor data brought by a low flying altitude still increases the capability of thermal cameras for accurate quantification of small objects such as human, fire centers, and pipe-leaking detection. Since temperature is highly dynamic, the thermal sensors are frequently used for real-time detection with a prior decision of the qualified capture rate. This, on the other hand, could be useful in RS and mapping when being integrated with sensors acquiring information from other spectrum ranges (i.e., visible bands and hyperspectral bands), and thermal infrared data are also employed for various agricultural and environmental applications. Examples include crop biophysical parameter estimation for precision farming and the use of UAV-based thermal camera to estimate water evaporation in a much finer spatial scale for irritation and water resource management.

Advantages: (1) well-targeted sensor for surface temperature measurement that drives a lot of new applications; (2) the camera model is normally perspective, and relatively easy to be processed than linear-array cameras. Disadvantages: (1) lack of texture information of its imageries brings difficulties in 3D reconstruction tasks; (2) for direct temperature measurement, it needs careful calibration; (3) cost is relatively high comparing to that of RGB cameras; (4) comparatively lower resolution than that of RGB cameras due to sensor design; (5) sensor compatibility to drones may be limited[16]

5.UAV LIDAR

LiDAR sensors have been known as one of the most accurate ways for geometric data acquisition. Widely used in forestry, cultural heritage, and building information modelling (BIM), the airborne, mobile, and terrestrial LiDAR nowadays have been well established in both the academia and industry.

Advantages: (1) direct geometric measurement; (2) multiple returns of the signals are useful for terrain modelling under thin canopies. Disadvantages: (1) high equipment cost; (2) highly dependent on expensive onboard GPS/IMU measurement (potentially with external reference stations); (3) increased payload for surveying quality LiDAR; (4) may not work in GPS-denied regions.[16]

6. Event Cameras: Event cameras are asynchronous sensors that sample light based on the scene dynamics, rather than on a clock that has no relation to the viewed scene.

Mueggler et.al[17] compared the performance of tradition CMOS camera and Dynamic Vision Sensor[DVS](Event Camera) by high speed drone maneuvers with respect to a static position.

Advantages of Event based sensors [17]:

- Sensitive to motion
- Responds to changes in scene on a pixel basis.
- High temporal resolution
- Low latency
- Low power
- High dynamic range (>120 dB)

Falanga et.al. [36] compared the performance of event camera and traditional vision sensor mounted on a drone, by hurling a soccer ball at a fast pace towards the drone. Not much difference between Event sensors and traditional vision sensor when the quadrotor is moving slowly. As the speed of the quadrotor increases, though, event cameras can start to make a difference. A quadrotor with a thrust to weight ratio of 20, achieved maximum safe obstacle avoidance speeds that are about 12 percent higher than if it was using a traditional camera.

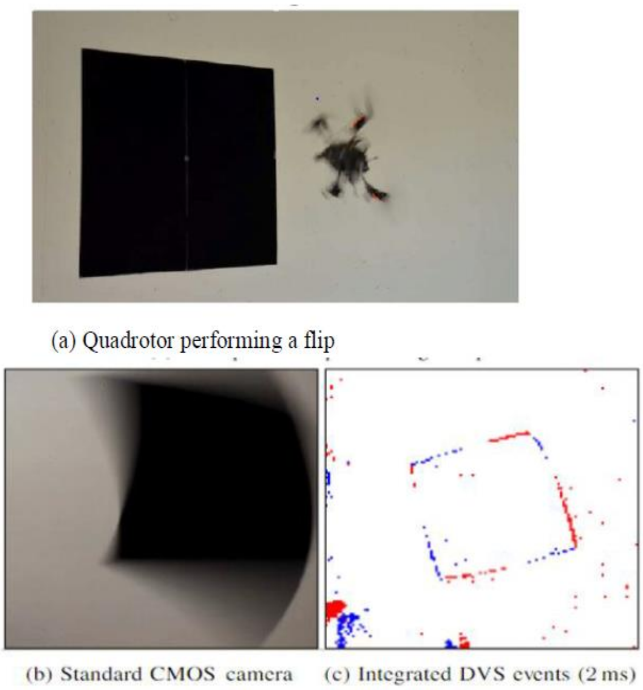

Fig- 5: Performance comparison of CMOS and DVS sensors[36]

5. ACTIVITY DETECTION

The concentration of this survey is on activity detection in aerial (Drone based) surveillance videos. A detailed description on works reported in literature has been comprehended.

1.Shark Detection: Butcher et al.[21] analyzed the reliability of drones to detect shark analogues in the water across a range of environmental conditions experienced on New South Wales beaches. 27 flights were made which encompassed a range of environmental conditions, including wind speed (2–30.0 km per hour), turbidity (0.4–6.4 m), cloud cover (0–100%), glare (0–100 and sea state (Beaufort Scale 1–5 Bf).Detection rates of the shark analogues over the 27 flights were significantly higher for the independent observer conducting post-flight video analysis (50%) than for the drone pilot (38%). Specifically, at a set depth of 2 m below the water surface, very few analogues were seen by the observer or pilot when water turbidity reduced visibility to less than 1.5 m. Similarly, when water visibility was greater than 1.5 m, the detection rate was negatively related to water depth.

2. Fire detection: Giitsidis et al.[22] proposed a method to detect human and fire from high altitude UAV images. For human recognition information like movement patterns as well as shadow size and shape are considered. For fire detection a blob detector is utilized in conjunction with a color based descriptor, applied to thermal and optical images respectively. The images are acquired vertically to the surface, which combined with the large altitude results in low numbers of features that can be used in order to detect humans. Both a full color and thermal optical sensor are used along with meta-data provided by the navigational portion of the UAV to improve the accuracy.

Burghouts et al.[23] developed a system to extract metadata about human activities from full-motion video recorded from a UAV. The pipeline consists of: tracking, motion features, representation of tracks in terms of their motion features and classification of each tract as one of the human activities of interest. The activities considered here are walking, running, throwing, digging and waving. The implementation was tested using UCF-ARG dataset and achieves an average accuracy of 93%.

3. Wildlife Poacher detection: Mendez et at.[24] developed an autonomous vision based unmanned aerial system against wildlife poachers. This work is focussed on development of capabilities for autonomous taking-off and following of a predefined position list, tracking animals, detecting poachers faces, tracking and following poachers' vehicles and return, via an autonomously- landing scenario, on specific stations in order to recharge the batteries and prepare for the next surveillance flight. Adaptive visual tracking algorithm is used to tract wildlife animals in their natural environment. The adaptive algorithm is tested with different aerial videos taken by quadcopters in Africa. One of the issues is that the detection is not always continuous. Results show that the root mean square error for the lateral, longitudinal, vertical and heading controllers on the first moving target-following was 8.6 degrees.

Bondi et al.[25] proposed SPOT (Systematic Poacher detector), an application that augments conservation drones with the ability to automatically detect poachers and animals in near real time. SPOT illustrates the feasibility of building upon state-of-the-art AI techniques, such as Faster RCNN, to address the challenges of automatically detecting animals and poachers in infrared images. This paper reports (i) the design and architecture of SPOT, (ii) a series of efforts towards more robust and faster processing to make SPOT usable in the field and provide detections in near real time, and (iii) evaluation of SPOT based on both historical videos and a real-world test run by the end users in the field. The promising results from the test in the field have led to a plan for larger-scale deployment in a national park in Botswana. While SPOT is developed for conservation drones, its design and novel techniques have wider application for automated detection from UAV videos. SPOT is evaluated on both historical videos and a real-world test run in the field by the end users, a conservation program called AirShepherd (AirShepherd 2017). SPOT method is compared with EyeSpy (Hannaford 2017) the application that is used in current practice that requires users to tune eight parameters to correctly identify objects of interest, plus six flight metadata parameters such as altitude and camera angle.

4. Rail Track Detection: Kumar Singh et al.[20] designed a vision based rail track extraction and monitoring system through drone imagery. Kumar Singh et al propose an approach for computing gauge measurement using drone imagery. The health of the tract is determined by applying computer vision techniques on drone data. Annotated computer vision mechanism for the railway inspection system provides fast and cost-effective way of detecting various anomalies present in the railway track. Inspection by drone does not require dedicated track for inspection hence does not affect the smooth running of trains. Aerial images with the camera oriented downward given convergence free view of track. The results of track monitoring over a month shows the increase in gauge measurement and hence decline in the health of the track.

5. Vehicle Detection: Tan et at. [26] presented a method for vehicle detection and classification in aerial imagery. Change detection analyses a pair of mutually aligned images captured at the same location but at different time instants to generate vehicle proposals. Next, a trained Convolutional Neural Network (CNN) classifier is applied to (1) determine if a proposal truly contains a vehicle, and (2) classify any vehicle present into major categories. Experimental results using infrared (IR) data demonstrate the efficacy of the method: vehicle detection rate is 99%; light-duty vehicles (e.g. sedan) are classified with 89% accuracy, medium-duty vehicles (e.g., van and pickup) with 79% and heavy-duty vehicles (e.g., trucks and buses) with 73% accuracies. The classification performance difference among different vehicle types is attributed to the size of training samples available in each category.

Sommer et al. [33] investigated the potential of Fast R-CNN and Faster R-CNN for aerial images, which achieved top performing results on common detection benchmark datasets. Therefore, the applicability of eight state-of-the-art object proposal methods used to generate a set of candidate regions and of both detectors is examined. RPN achieved the best performance of all proposal methods. They performed their experiments on the publicly available DLR 3K Munich Vehicle Aerial Image Dataset and Vehicle Detection in Aerial Imagery (VEDAI) dataset. The best detection performance was achieved for Faster R-CNN that shares the convolutional layers with the RPN. Precision of detection is 88.7%,it is computationally expensive and bigger object is easy to detect compared to humans.

Deng et al.[34] proposed a fast and accurate vehicle detection framework. On one hand, to accurately extract vehicle-like targets, they developed an accurate-vehicle-proposal-network (AVPN) based on hyper feature map which combines hierarchical feature maps that are more accurate for small object detection. On the other hand, they proposed a coupled R-CNN method, which combines an AVPN and a vehicle attribute learning network to extract the vehicle's location and attributes simultaneously. For original large-scale aerial images with limited manual annotations, they used cropped image blocks for training with data augmentation to avoid overfitting. Comprehensive evaluations on the public Munich vehicle dataset and the collected vehicle dataset demonstrated the accuracy and effectiveness of the proposed method compared to other methods.

Method	Ground Truth	True Positive	False Positive	Recall Rate	Precision Rate	F1 Score
ACF detector	882	382	652	43.31%	36.94%	0.40
SS+fast R-CNN	882	291	864	32.99%	25.19%	0.29
Faster R-CNN	882	395	**149**	44.78%	**72.61%**	0.55
AVPN_basic	882	**452**	171	**51.25%**	72.55%	**0.60**

Figure 9: Result of different methods on collected vehicle dataset[34]

ElMikaty et al. [35] presents a framework for the detection of cars in high-resolution aerial images of complex urban environments scenes. The proposed framework consists of two main sub-systems: window evaluation and window classification. The performance of the proposed framework was assessed on the Vaihingen dataset using the precision-recall curves, the average precision and the interpolated average precision. In heavily-cluttered environments, e.g., urban environments, the existence of many objects that are visually similar to cars can produce a high rate of false positives. In the proposed framework, it was shown that an approximate extraction of roads can be achieved using a Gaussian Mixture Model that is taught to distinguish pixels based on colours.

6.UAV tracking: Heintz et al.[27] proposed a UAV tracking and monitoring application for achieving high level situation awareness about traffic situations in an urban area. It takes as input sequences of color and thermal images which are used to construct and maintain qualitative object structures and to recognize the traffic behavior of the tracked vehicles in real time. The system is tested both in simulation and on data collected during test flights. To facilitate the signal to symbol transformation and the easy integration of the streams of data from the sensors with the GIS and the chronicle recognition system, DyKnow, a stream-based knowledge processing middleware, is used. It handles the processing of streams, including the temporal aspects of merging and synchronizing streams, and provides suitable abstractions to allow high level reasoning and narrow the sense reasoning gap. The traffic monitoring application has been tested both in simulation and on images collected during flight tests. As per the result in order to detect car overtakes on road reliably 100 ms sample period is required.

Prithviraj Dasgupta [28] proposed a Multiagent Swarming System for Distributed Automatic Target Recognition Using Unmanned Aerial Vehicles. In this method, a multiagent-based prototype system is described that uses swarming techniques inspired from insect colonies to perform Automatic Target Recognition (ATR) using UAVs in a distributed manner within simulated scenarios. It is assumed that UAVs are constrained in the resources available onboard and in their capabilities for performing ATR due to payload limitations. The focus here is on the coordination aspects between UAVs to efficiently decide how they are to act by using a swarming mechanism. Algorithms for the different operations performed by the UAVs in the system and for different swarming strategies are described, which are embedded within software agents located on the UAVs. Simulations of the system within a simulated area of interest is performed to determine its behaviour in different scenarios with varying operational constraints. Experimental results indicate that swarming strategies for distributed ATR perform favourably compared with centralized ATR strategies.

Rozantseva et al. [29] proposes an approach to detect flying objects such as UAVs and aircrafts when they occupy a small portion of the field of view, possibly moving against complex backgrounds, and are filmed by a camera that itself moves. Solving such a difficult problem requires combining both appearance and motion cues. A Regression-based approach is proposed to motion stabilization of local image patches that allows to achieve effective classification on spatio-temporal image cubes and outperform state-of-the-art techniques. Two challenging datasets are collected for UAVs and Aircrafts, which can be used as benchmarks for flying objects detection and vision guided collision avoidance. Average precision for the method experimented on UAV dataset is 0.751 and the average precision while experimenting using Aircraft dataset is 0.789.

7. Landmine detection: In [30] a low-cost UAV for land-mine detection has been developed. The vision algorithm performed noise filtering using morphological operators and feature extraction with a template matching method. The classification process decided whether the detected target was object of interest or not.

8. Street Detection:

In [31] a vision-based system for street detection by a low-altitude flying UAV has been presented. The street identification was processed by a Bayes classifier to differentiate between street and background pixels. The street classifier updated its parameters from a recursive Bayesian process. When the street was identified an edge detection algorithm computed every object inside it and estimated a color profile. This profile was incorporated to the classifier in order to improve the parameters for street detection.

9. Animal/Bird Detection:

Fang et. Al [32] proposed for moving animal detection by taking advantage of global patterns of pixel motion. In the video dataset, where animals make obvious movement against the background, motion vectors of each pixel are estimated by applying optical flow methods. A coarse segmentation then removes most parts of the background by applying a pixel velocity threshold. Based on the segmented regions, another threshold was employed to filter out negative candidates that could belong to the background.

species	Total Frames	Ground Truth	True Detection	False alarm	False positive	False Negative
zebras	448	4102	3365	96	2.03%	17.97%
antelope	145	992	879	124	12.50%	11.39%

Fig- 10: Detection Performance[68]

This method is sensitive to animal movement and takes little account on other features such as the size, colour and shape appearance of the animal.

Hong et al. [34] constructed deep-learning-based object-detection models with the aid of aerial photographs collected by an unmanned aerial vehicle (UAV). The dataset containing the aerial photographs included diverse images of birds in various bird habitats and in the vicinity of lakes and on farmland. In addition, aerial images of bird decoys were captured to achieve various bird patterns and more accurate bird information. Bird detection models such as Faster Region-based Convolutional Neural Network (R-CNN), Region-based Fully Convolutional Network (R-FCN), Single Shot MultiBox Detector (SSD), Retinanet, and You Only Look Once (YOLO) were created and the performance of all models was estimated by comparing their computing speed and average precision. The test results showed Faster R-CNN to be the most accurate and YOLO to be the fastest among the models. The combined results demonstrated that the use of deep-learning-based detection methods in combination with UAV aerial imagery is fairly suitable for bird detection in various environments.

3. CONCLUSIONS

In this paper, we have presented a detailed survey of various drones types with different camera options available in market. A complete survey of state-of-the-art techniques for activity detection in drone captured videos has been done, which includes activities or objects like shark activity, fire, wild-life poacher activity, rail track, vehicle movement, UAV tracking, landmine, street, animal/bird.

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