Automatic Independent Video-based Air Traffic Surveillance system (AIVATS)

August 2020 – April 2021

Design Challenge: ***Airport Management and Planning***

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1. Executive Summary

The primary method of air traffic monitoring at airports is control towers. However, non-towered airports are the most common airport types across the world as well as the United States. As a result, there is no supervised monitoring system at most airports. In this proposal, the University of Utah research team presents an automatic system for monitoring air traffic at non-towered airports. The proposed system leverages video footage captured from the airport airfield and empowers them with computer vision to recognize and keep records of flight operations. Considering its fully vision-based framework, this system does not rely on any auxiliary electronic unit mounted on aircraft. Therefore, the low equipage rate of the aviation fleet has no adverse effect on the system application and accuracy. Implementation of such a system provides the airport managers and aeronautics divisions with accurate aircraft operation count, flight status, and fleet mix information. This information is essential for airport improvement plans and federal/state funding allocations. Moreover, the proposed system supports the visual clearance of the runway two ends, thereby increasing spatial awareness in the airport aerodrome.

Industry experts and airport operators were engaged throughout the design procedure. In addition to developing the technical side of the technology, the design procedure encompasses an exhaustive analysis of safety risk assessment and cost-benefit associated with the system implementation. The results hold a promise of having an accurate, safe, and beneficial system for the airport industry.

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3. Background and Problem Statement

The primary method of airport environment monitoring is the airport control tower. An air traffic control tower's role is to identify and keep records of aircraft operations and efficiently coordinate aircraft and vehicle operations on the airport field. It is noteworthy that non-towered airports—those not served by an operating air traffic control (ATC) tower—are much more common than towered airports. In fact, nearly 20,000 airports in the United States are non-towered, compared to approximately 500 that have towers (AOPA, 2021). While there is no accurate air traffic monitoring system at non-towered airports, alternative methods must be used to maintain safety and keep records of their air traffic. A part of the outcome will later be used as a basis for funding plans, resource allocations to airport industries, and airport performance assessment. The fleet mix information at these non-towered airports is important since different aircraft types operation emits a different level of air pollutants and noise. Considering these needs at non-towered airports, an automatic air traffic monitoring system can provide the managers with air traffic data and the operators/users with spatial awareness in the airfield, minimizing the chances of runway incursions. Billings (1997) used terms such as safety, reliability, economy, and comfort to state aviation automation benefits.

Within the current automatic technologies being used to monitor airport operations, General Audio Recording Device (GARD) is an electronic tracking data system that records the number of operations at the airports using radio traffic. The airport managers later use this data to calculate the airport's operational activity (Invisible Intelligence, 2021). Although it is an advancement in recording flight operations, it cannot recognize any aircraft that does not provide radio communication. Also, this system does not identify the aircraft identity, nor is it able to provide a real-time assessment of the airport runway to guarantee the operation (landing/ taking off) safety. Radio click counting (RCC) is an example of radio transmission systems for aircraft operation estimation. The RCC system counts the microphone clicks in each aircraft, where every 3 to 4 clicks correspond to one aircraft. In this way, it is possible to estimate how many aircraft are operating, but the system cannot distinguish the aircraft operation (either landing or departure), nor can it provide an accurate and reliable operation record.

Another current technology that has been implemented in the air traffic system is Automatic Dependent Surveillance-Broadcast (ADS–B). It consists of a technology in which an aircraft determines its position via satellite navigation and periodically broadcasts it to the air traffic control ground station or other aircraft, enabling it to be tracked and allowing self-separation (Airservices Australia, 2012). Despite the advantages, this system requires an optimum site with an unobstructed view to aircraft, and some outages are expected due to poor GPS geometry when satellites are out of service (Koh, 2019). With an attempt to supplement the automatic dependent surveillance for the operation count task, image detection was added to the system for recognizing aircraft while taxiing into the centralized terminal, which had been initially developed only for automating the landing fee bill charges. The new system was called VID/ADS-B, which stands for Video Image Detection / Automatic Dependent Surveillance-Broadcast. Although VID/ADS-B was able to detect taxiing aircraft into the terminal at a moderately low error of approximately 17%, it did not successfully and effectively perform the operation count task. The VID/ADS-B failure reasons are but not limited to counting dependency on ADS-B out units on aviation fleet, extravagant cost, inherently missing touch-and-go flight activities, and being conducive only for a specific airport layout plan (with limited access to the terminal area) (ACRP Report 129, 2015). That said, our proposed system aims to provide an uninterrupted ground-based operation monitoring using a video-based system, which does not require a GPS signal or radar to count and identify the aircraft (type, make, model, etc.) and the operation status (departure/arrival) at airports. The proposed independent system is flexible to different airport layout plans and has a solution for capturing touch-and-go operations as well.

In this proposal, our automatic independent video-based air traffic surveillance system (AIVATS) has a solution for all airport types (with centralized and un-centralized terminals). Cameras at strategic locations at the host airport are the required hardware of this video-based air traffic surveillance solution (Figure 1). In this proposal, we discuss using low-cost hardware devices for future AIVATS system development. The designed software empowers them with autonomous system characteristics using computer vision. By being an autonomous air traffic surveillance system, AIVATS consists of the implementation of a video-based system to automatically detect aircraft, track/count the aircraft operations (both on-the-ground level and off-the-ground level), distinguish departure operations from landing operations, and identify aircraft by its tail number. All these tasks are done independently by the developed software and cameras' footage, with no need for external auxiliary electronic devices mounted on the aviation fleet. Autonomous systems introduce a level of flexibility that allows service levels to be enhanced (Frequentis, 2016); runway ends visual clearance delivery is a service enhancement instance for AIVATS.

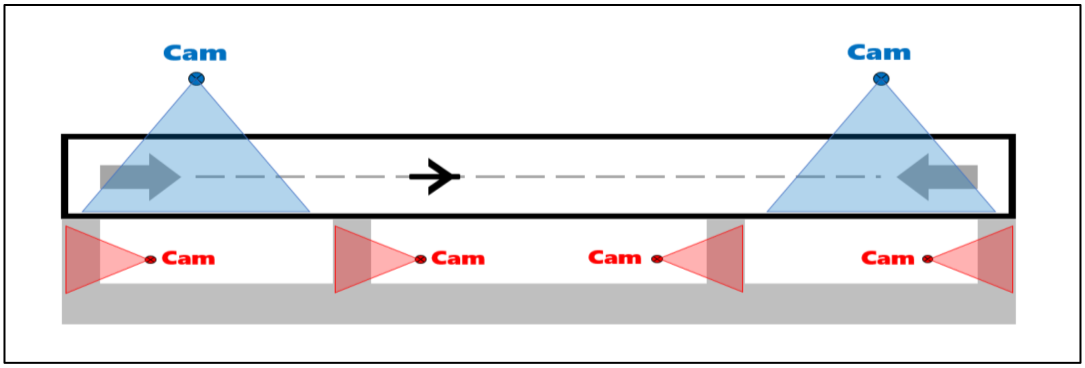

Figure 1. Camera layout 1 (blue colored), and layout 2 (red colored) in the airport

This project aims to assist in the monitoring of aircraft operations for airports that do not have ATC towers. Our proposed system will keep records of aircraft operations using cameras deployed in the airport. Figure 1 depicts the proposed system, which includes two independent camera deployment layouts. The detailed camera coordinations are in camera layout plans subsection in section 6. As such, each layout will provide airport air traffic information, enabling managers to plan for maintenance and repairs based on the actual airport traffic load. Additionally, when the system detects an aircraft, it can provide operators and users with clearance status of the two runway ends, preventing runway incursions. The outcome data is useful for airport owners, managers, pilots (airport users), and basically, everyone involved with airport operations.

4. Literature Review

4.1. Air Traffic Monitoring Impact

There are a few technologies being used to monitor aircraft operations (i.e., to track, count, distinguish, and identify). According to Johnson and Gu (2017), it is crucial to keep records of the number of aircraft operations (take-offs and landings) annually, once this operations data is heavily used when developing airport master planning, conducting airport environmental research, forecasting economic impact, adjusting funding, and measuring aviation performance. In addition, operation counts are reported on the FAA Airport Master Record Form 5010 (FAA, 2016). At towered airports, aircraft operations are counted during tower hours. On the other hand, at non-towered airports, aircraft operations are estimated based on sample counts or other methods (Johnson and Gu, 2017). The primary method of tracking and counting aircraft was based on radio transmission data, such as radar. The current systems in practice, which are also briefly reviewed in the problem statement, are ADS-B, GARD, and RCC.

4.2. Radio-based and Acoustical Systems

The ADS-B system determines the aircraft position via satellite and periodically broadcasts it, enabling it to be tracked in real-time by the ATC and other aircraft with ADS-B hardware. It is an automatic monitoring system since it does not need the pilot’s input but the data from the aircraft’s navigation system (FAA, 2019). On the other hand, the GARD system monitors the airport flights at a determined frequency and collects data from take-offs and landing operations. The system uses the airport UNICOM frequency to record audio transmissions, using the average number of transmissions made by each aircraft, which counts them as one operation (Parlin Field, 2014). A downside of this technology is that GARD only monitors one frequency per unit (Invisible Intelligence, 2021), so it would be necessary for many devices to monitor different frequencies. One common issue with these systems (including RCC) is the use of radar and/or radio information. As a result, these systems rely on externally provided input data and tend to be inaccurate due to data transmission interruptions and noises. The use of acoustical counters, which only use the aircraft sounds while taking-off, leads to obtaining less accurate operation flight data and missing all landing operations. Examples are missing a single-engine aircraft operation at a distance of 50 feet of the acoustic counter unit (ACRP report 129, 2015). The counter may mistakenly count any other nearby aircraft that is not necessarily taking off or landing. For long runways, multiple counters are needed, which makes it more labor-intensive. Also, no information on aircraft type and model is provided by such systems (ACRP report 129, 2015). To that end, an image-based method can be used.

VID/ADS-B was introduced to assist ADS-B in counting the aircraft operations. It tracks aircraft using supplemental FAA electronic-based near real-time traffic data from the National Airspace System (NAS) known as the Aircraft Situation Display to Industry (ASDI). However, VID/ADS-B use is restricted to only airport layout plans with centralized terminal and hanger areas with limited access points and is not applicable in airports with dispersed terminal/hanger configurations (ACRP report 129, 2015). Indianapolis Executive Airport (TYQ**)** was for the first time tested for VID/ADS-B implementation (ACRP report 129, 2015). Muia (2015) declares that this system was not compatible with the other intended test locations, Eagle Creek Airport and Purdue University Airport. This system is unable to count touch-and-go operations. The transponder receiver also failed to perform well and had 100% error during the observation for the TYQ field trial test. Moreover, VID/ADS-B cost totaled high, anywhere from $50,000 to over $150,000 depending on the airport layout plan plus the monthly charge from the technology provider to obtain the flight data. ADS-B based methods are not still suggested as an effective method for operation count due to the low equipage rate of the aviation fleet with ADS-B out units (FAA, 2021).

4.3. Vision-based Systems

A vision-based surveillance system can independently tackle the aforementioned needs at airports. Besada et al. (2001) proposed a surface surveillance system based on CCTV cameras pre-installed in airports. Their proposed system performs aircraft and vehicle mobile positioning and tracking based on a foreground-background separation algorithm (using blob analysis) which usually is highly sensitive to camera movements and does not yield robust detections. Additionally, the use of CCTV/security cameras can only help position aircraft in their field of view and cannot capture and recognize the aircraft in operation to keep the flight records.

On the other hand, a fully automatic video-based system can provide an air traffic monitoring service independently. This proposal presents an independent vision system named AIVATS to monitor the aircraft operations in the airport environment. AIVATS has two layouts (with two camera deployment plans) in airports and is able to detect, track, classify, and identify an operating aircraft independently. This system is adaptable for different airport configurations and does not rely on external auxiliary unit input such as ADS-B out and ASDI.

Not only can such a system count the operations and deliver runway clearance, but it also can detect and identify the aircraft using the printed tail number on the aircraft's body. On layout 1, one camera is positioned near each end connectors towards the runway so that arrivals and departures can be captured from the runway two endpoints.

The arrival operations will be off-the-ground level, and the departure operation on-the-ground level. This process uses a video frame-by-frame aircraft detection method. If an aircraft is detected using the embedded object detection algorithm, the processing software activates the visual tracking module that subsequently classifies the aircraft movements into either departure or arrival operations. This will then add to the operations count of the total number of landing or take-off operations. Moreover, the system uses optical character recognition methods to detect and read the tail number of the aircraft, identifying it, making it possible to match with the FAA (Federal Aviation Administration) database.

Layout 2 performs the same steps as the previous one, but the cameras are positioned toward runway connectors to monitor the taxiing aircraft from/towards the runway. It gives a better chance for reading the aircraft's tail number since the aircraft is closer and moving slower than operations captured in layout 1. AIVATS layout 1 accurately can count the number of operations. The test results are assessed in section 6. It should also be noted that AIVATS layout 1 can work independently and keep records of touch-and-go operations. In cases of need for higher aircraft identification accuracy, layout 2 can be implemented both independently and jointly, which also helps with finding the percentage of touch and go operations in an airport as a spinoff use.

The problem-solving approach section reviews each sub-element of the proposed system, including aircraft detection, tracking, and identification. The conducted research works are critically assessed for each sub-element, and the best approach is adopted and developed for addressing the system sub-element's requirements. As for the future of the AIVATS development, section 6 (system principle section) also assesses the low-cost hardware devices that can be used as the system platform.

5. Design Problem-Solving Approaches

In this section, image recognition challenges regarding aircraft detection, tracking, and identification are discussed. Accordingly, solutions are devised to address the image recognition requirements for use in an airport automatic video-based air traffic surveillance system.

5.1. Aircraft Detection

Detecting the operating aircraft in the camera field of view is the first step toward the autonomous air traffic monitoring system. Extensive research work (Alganci et al. 2020, Chen et al. 2018, and Xu et al. 2018) is conducted for detecting airliners from remote sensing images, which are different imagery data from a ground-based camera layout in an air traffic surveillance system. Dey et al. (2011) and Fu et al. (2014) proposed a rapid aircraft detection and tracking method using multiple classifiers for unmanned aerial vehicles (UAV) sense and avoid systems. Since their proposed methods are to avoid flying aircraft by UAVs in the sky, they did not consider aircraft detection in cluttered environments such as the near-surface of the airport, nearby ground traffic, and possible construction equipment. In contrast, departure operations take place on the near-surface of the airport with a complex background in the footage (Figure 2).

Figure 2. Aircraft detection in a video frame with a complex background

Alternatively, to implement an accurate aircraft detection module in our system, we use deep neural networks (DNNs). In particular, several convolutional neural networks (CNN)-based methods have been proved to achieve state-of-the-art object detection, for instance, Region-CNN (R-CNN) (Girshick, 2014). Even though R-CNN is able to present high accuracy, the process is slow and difficult to optimize. That considered, YOLO (You Only Look Once) (Redmon, 2016) and SSD (Single Shot Detector) (Liu et al. 2016) are the two selected candidates, as they have shown high performance in a range of different applications, outperforming existing approaches regarding object detection speed while preserving a good accuracy. YOLO diminishes the computational complexity issues associated with R-CNN by formulating the object detection problem as a single regression problem. The main difference between YOLO and SSD networks is the absence of fully connected layers at the end of the SSD's network.

5.2. Aircraft Tracking

Tracking is the task of locating an object in successive frames of a video after first detecting the object. Rastegar et al. (2009) developed a method for airplane detection and tracking based on wavelet transform and SVM (Support Vector Machine) classifier.

The proposed method uses both color and spatial information obtained from the image. However, Rastegar's method works well for pixel-level classification and does not yield accurate tracking, especially for localizing the aircraft after the first detection. Detecting and tracking aircraft below the horizon might present different challenges, such as a more complex background induced by the airport environment's nature.

Considering the background complexity, a robust tracking algorithm is required to ensure consistent results. MOSSE (Minimum Output Sum of Squared Error) (Bolme et al. 2010) is a fast-tracking algorithm, which is robust to variations in lighting and poses at the same time. These characteristics make MOSSE a proper choice for the task of aircraft tracking in an autonomous air traffic control system. Figure 3 shows the result of tracking an arrival operation in layout 1 using MOSSE after detecting the aircraft with the aircraft detection module.

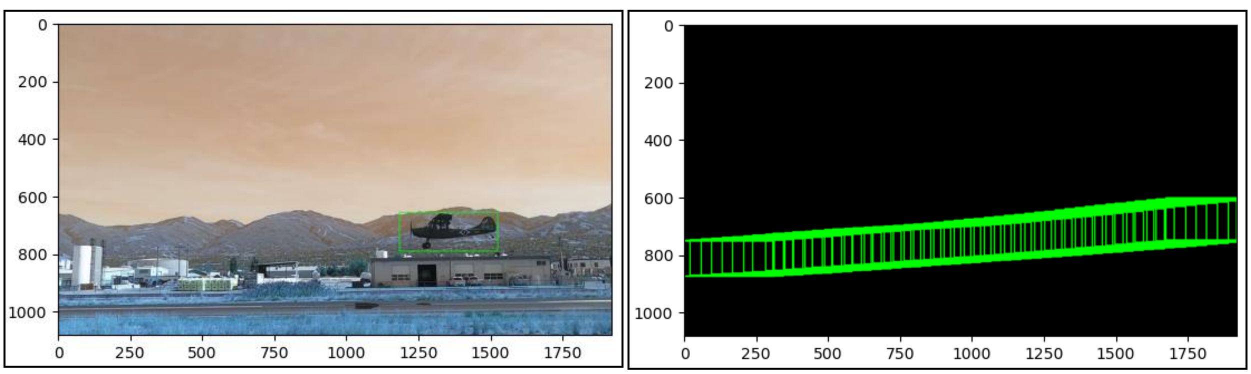

Figure 3. Left: Detecting aircraft in a video frame, Right: Tracking the detected aircraft in the consecutive video frames

5.3. Aircraft Identification

How to identify aircraft from its image? Tail numbers are the answer. Molina et al. (2002) proposed a method for detecting the tail number of airliners and subsequently reading it for Advanced Surface Movement Guidance and Control Systems. Their proposed method uses the captured images from stationary airliners to localize the tail number region zone using the contrasting regions (letters) in the grayscale image. As a result, the proposed method most likely does not perform well for identifying aircraft in operation (I.e., in motion) since any movement results in blurry images. Molina's proposed image processing algorithm searches over several extracted sub-images from the original image of the stationary airliner and limits the potential candidate using a two-level contrast threshold detector. The binary images resulted from thresholding are then reprocessed with a blob growing algorithm to accentuate the possible character pixels. After repeating the described steps several times, the zones that are present in several sub-images are selected as the tail number region candidate, and the target zone will be the highest voted one. The recognition then is proceeded with the integration of a feature-based OCR and FAA database, where they convert the problem into a vector classification to solve the problem. Although this method promised a high recognition accuracy for airliners, it cannot work well for all aircraft types, namely light aircraft. Molina's method is based on symmetric and standard letter style tail numbers printed on the body of airliners, which are much bigger than light aircraft (Figure 4, left). When there are many visual variations such as aircraft poses while landing/departing and inclined tail numbers with different font shapes and sizes (Figure 4, right), deep learning-based detection can help increase text detection/recognition accuracy in the natural scene.

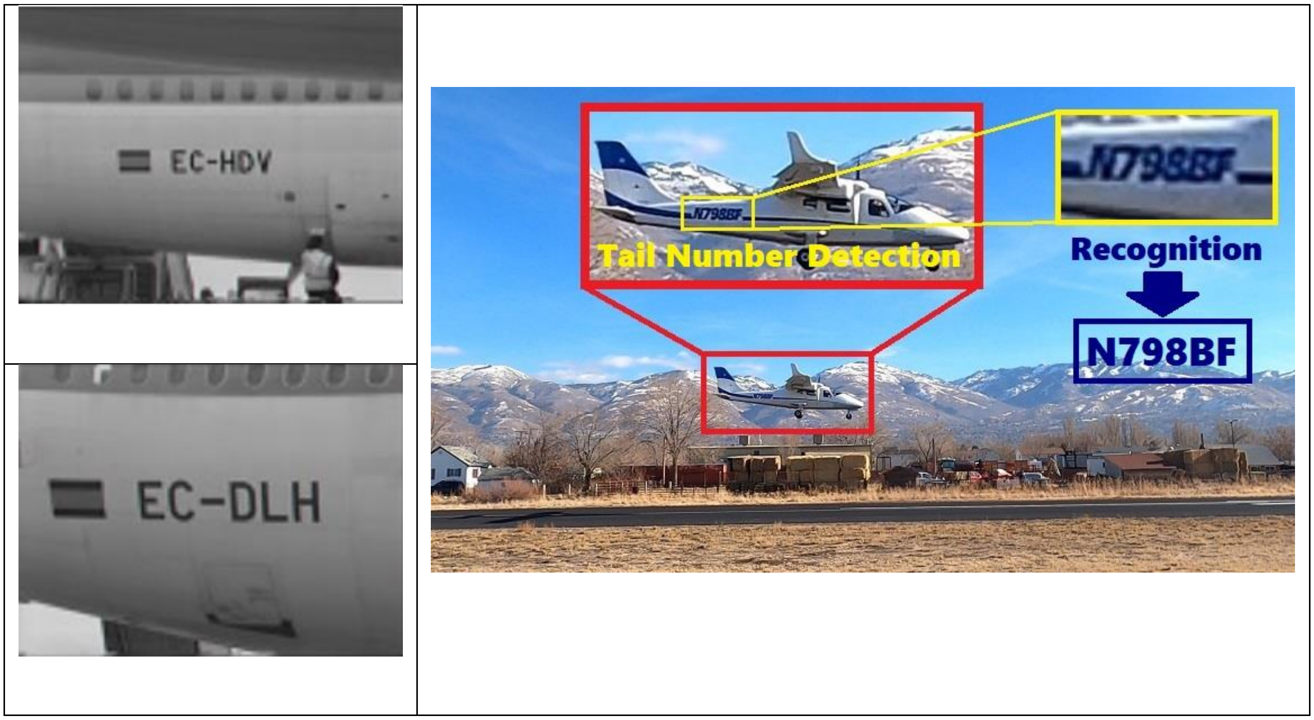

Figure 4. Left: Images from airliners' tail numbers (Molina et al., 2002), Right: A video frame of an aircraft in motion (landing, camera layout 1)

That being said, we chose a DNN based text detection and recognition to be embedded in our software for the air traffic monitoring system. For the task of text region detection, the TextBoxes network (Minghui 2017) is selected for its accurate and fast detection. The Convolutional Recurrent Neural Network (CRNN) (Shi et al. 2016) is the backend of the software's tail number recognition module. These two networks provide an accurate tail number identification as long as the tail numbers are not very small and not cluttered with random lines printed on the aircraft body.

6. System Principle

6.1. Camera Layout Plans

After careful observation of the various existing airport layout plans and interaction with local airport operators, two possible camera layouts for the small airports are proposed, each with different data capturing setup and requirements. An air traffic surveillance system aims to record all flight operations in an airport. Aircraft pilots run from the end of the runway to add a safety margin for a stop on the runway in case of an engine failure/rejected take-off. Therefore, two ends of the airport runway are designated as strategic points for camera placements in layout 1 to capture flight operations (Figure 5, top). As explained and Figure 5 (bottom right) shows, departure operations, which start from either end A or end B, are captured on the ground level in the provided field of view. Accordingly, the arrival operations are taken while landing, although still off the ground level (Figure 5, bottom left).

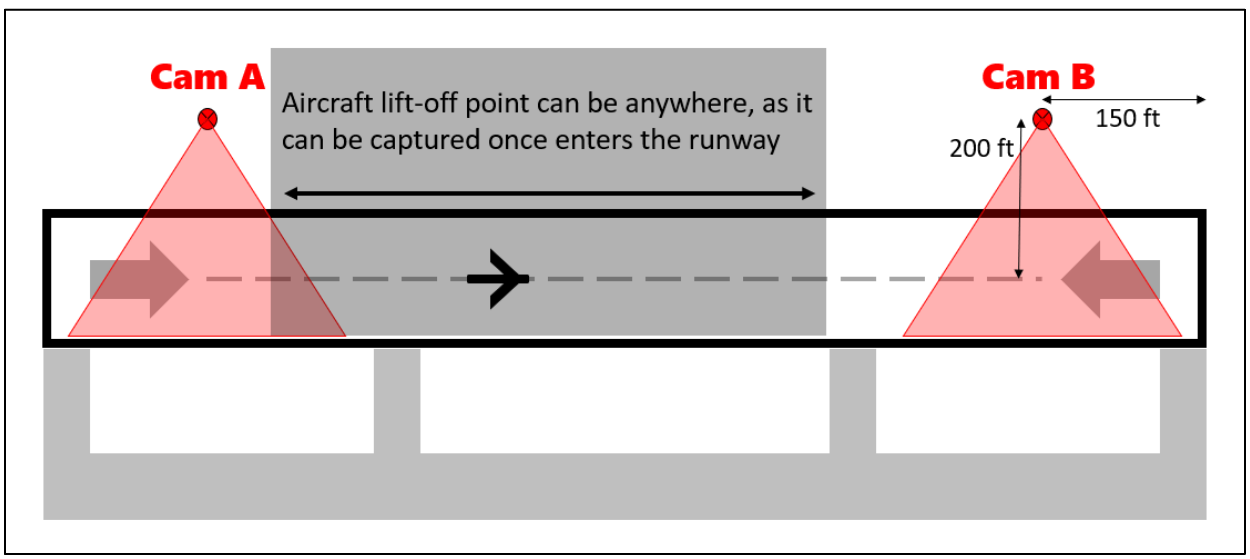

Figure 5. Top: Camera deployment in layout 1, Bottom: Field of view in Camera A for an arrival operation (left) and a departure operation (right) on the runway area

While layout 1 is capable of having all flight operations, including touch-and-go activities, some aircraft operations might not be visually identifiable in its field of view (Figure 6: Difficult to read the tail number for identification purposes). That considered, layout 2 is designed for cases with higher recognition accuracy provided by layout 1. Figure 7 demonstrates the camera placements and orientations in the airport for layout 2.

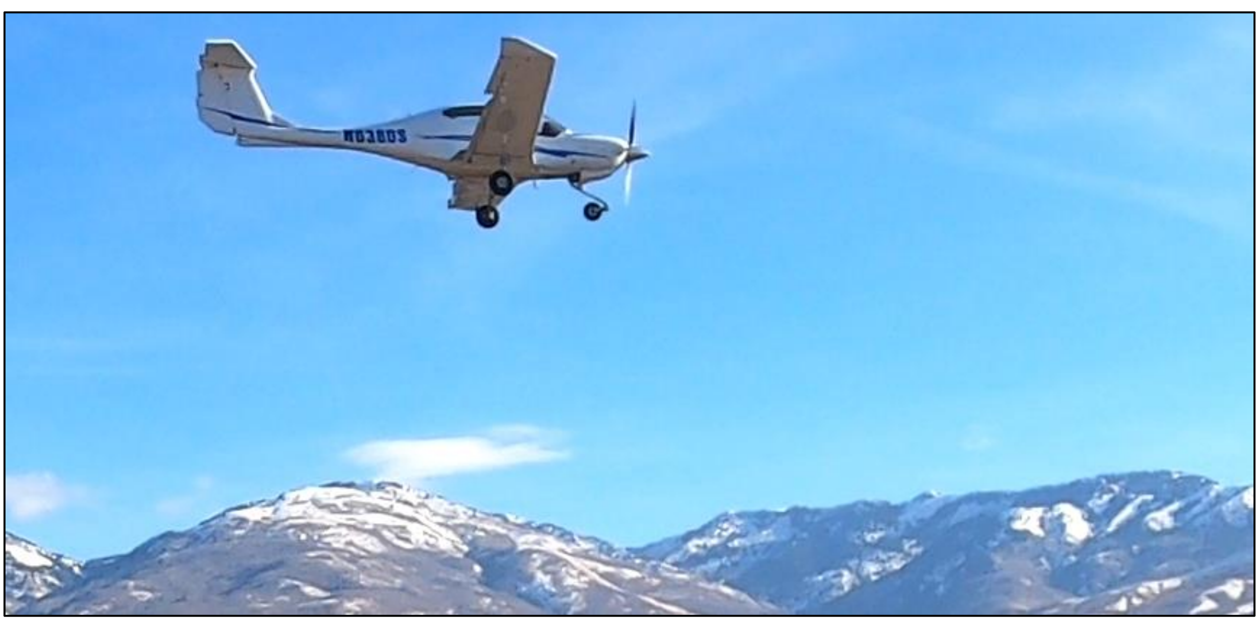

Figure 6. View of a landing aircraft with a difficult-to-read tail number in layout 1 FoV

Since any operation needs a passage over connectors, layout 2 FoVs view flight operations (either departure or arrival) on the ground level and is able to distinguish them based on the aircraft motion direction in the respective connector.

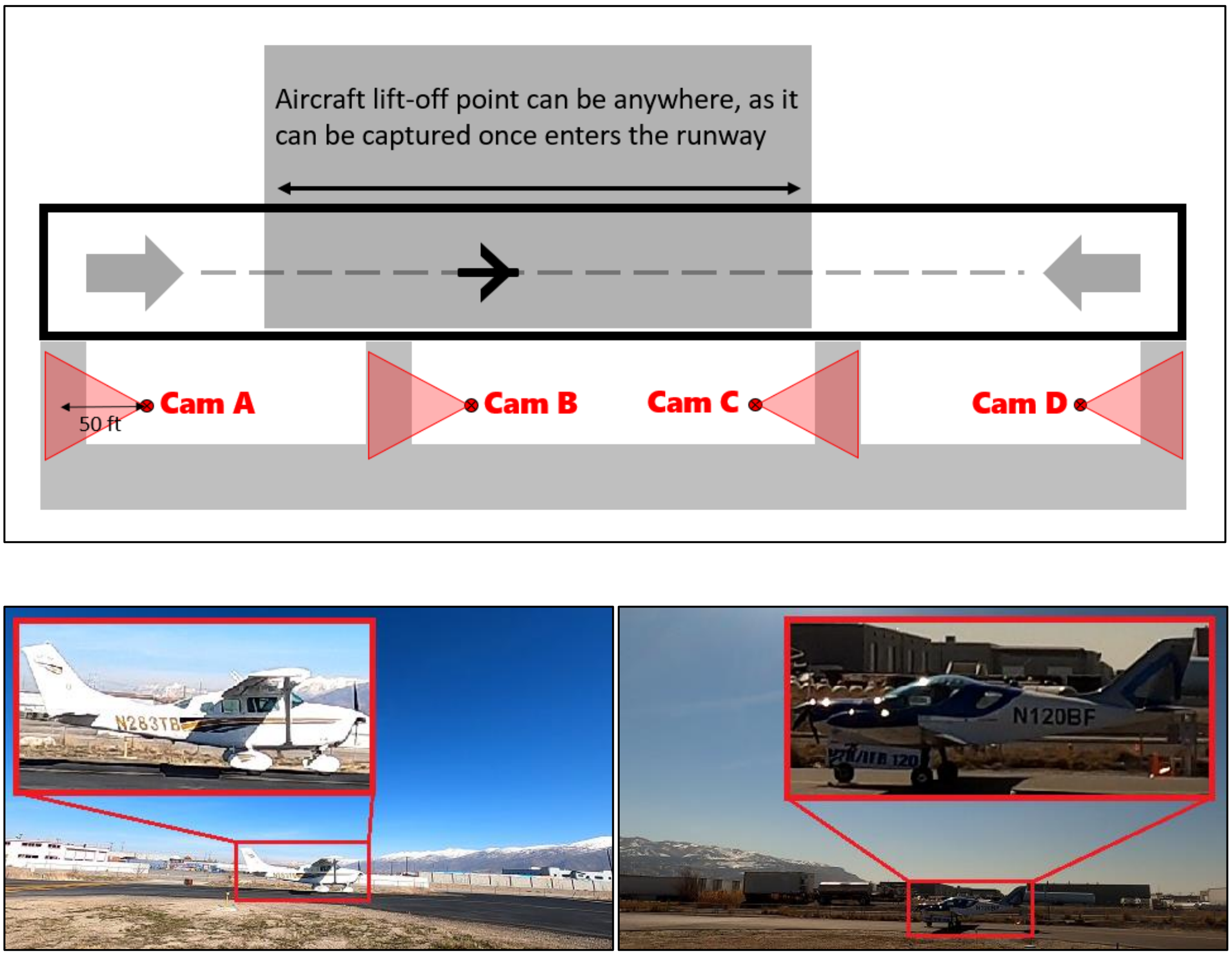

Figure 7. Top: Camera deployment in layout 2, Bottom: Field of view in Camera A for a departure operation (left) and an arrival operation (right) on the taxiway-runway connector area

As a spinoff use, layout 2 can be used for finding touch-and-go activities' occurrences as well. To that end, the counted arrival operations at connector passages are subtracted from all landing aircraft operations seen at the end connectors (Cam A and D in Figure 7). Figure 8 shows the Cam A field of view for a landing operation. Table 1 illustrates air traffic visual data details provided by each camera layout separately.

Figure 8. Landing aircraft in layout 2 Cam A (end connector FoVs)

Table 1. Typical visual data field provided by camera layout 1 and layout 2

Visual data set field	Layout 1	Layout 2
Able to count all flight operations	✓	✓
Able to distinguish departure operations from landing operations	✓	✓
Able to count touch-and-go activities	✓	✓
Able to capture aircraft tail number for departure and arrival operations	✓	✓
Able to capture aircraft tail number for touch-and-go activities	✓	✗
Able to distinguish touch-and-go activities from non-touch-and-go arrival operations	✗	✓

The test locations are three public-use airports in Utah: Bountiful Airport, Brigham City Municipal Airport, Spanish Fork Airport. The dataset was collected with a low-priced commercial off-the-shelf camera (GoPro Hero 8, Figure 9) recording with 1080 video resolution and 30 frames per second to ensure enough pixel and number of frames in a flight operation time window for aircraft identification.

Figure 9. GoPro Hero 8 camera setup

6.2. Software Development

There are non-operational activities included in the airport video footage in both layouts. Nearby ground traffic (either inside the airport or outside the airport) and construction activities at some airports are examples. Also, the aircraft approach trajectories vary for different aircraft at the airport aerodrome. Aircraft in motion and at some cases with high speed (landings) are other challenges that must be considered while compiling the software backend. Therefore, a multistage design is developed for the software. Figure 10 illustrates the software backend flowchart from the video feed to the flight status recognition and aircraft operation identification.

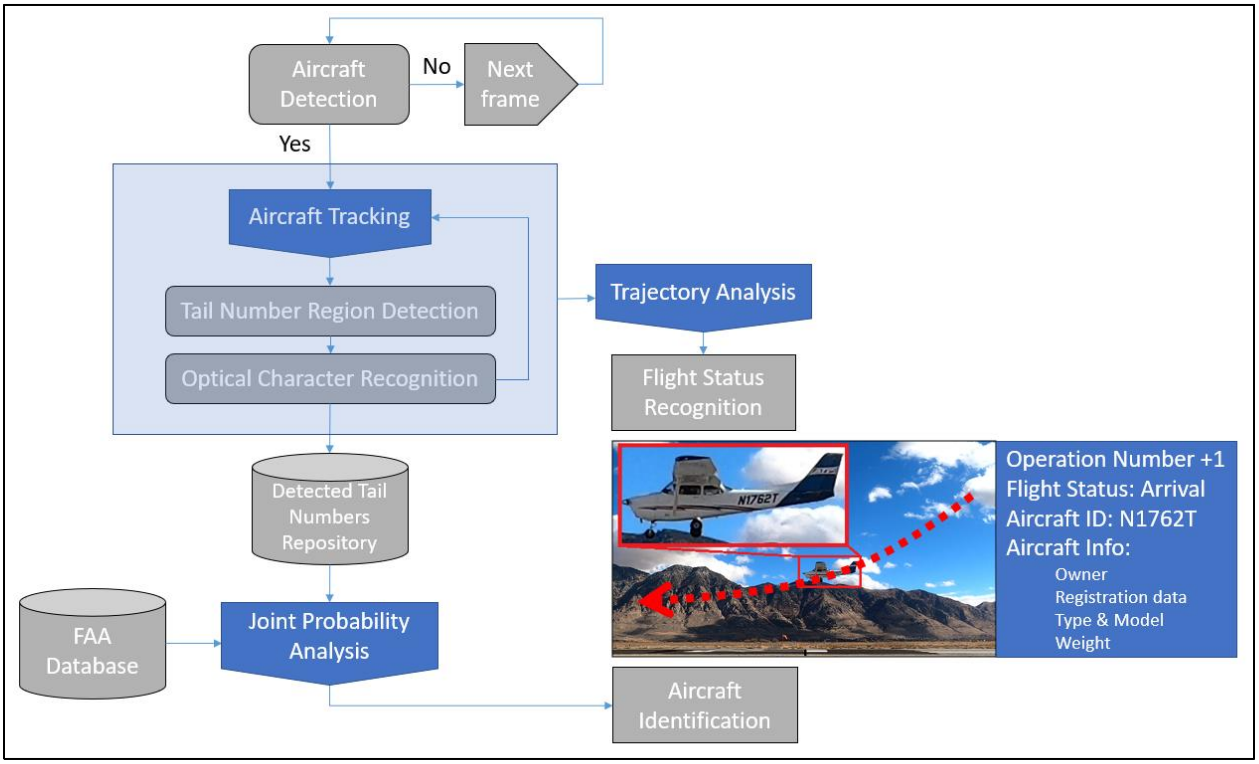

Figure 10. Software flowchart

The core software modules include aircraft detection, aircraft tracking, tail number region detection, tail number recognition, and joint probability analysis. The remainder of this section discusses the implementation of each module.

Regarding the aircraft detection module, two neural networks are selected to be used for camera layouts. YOLO machine learning package, which promises very accurate detections, is implemented for layout 1. On the other hand, layout 2 provides a closer range of view, so it can be benefited from a faster detector that needs larger objects for detection in the scene named SSD. YOLO and SSD trained models on the Microsoft COCO dataset (Lin et al. 2014) are implemented in Python using the OpenCV (*Open Source Computer Vision Library*) (Pulli et al. 2012) deep neural networks module.

The software tracks the detected aircraft using a fast-tracking algorithm named Minimum Output Sum of Squared Error (MOSSE). The tracking output is a trajectory associated with the operation of the detected aircraft. This trajectory is then analyzed to distinguish the departure operations from arrival operations. To that end, four variables are extracted from the provided trajectory, and a threshold value is set for each variable to classify the operations into arrivals or departures. These variables are the average pixel value of the aircraft trajectory, the standard deviation of the aircraft trajectory, aircraft operation speed, and aircraft speed uniformity during the observation of the aircraft operation. Each variable gets a vote, and the most-voted flight status determines the operation status (i.e., either departure or arrival). Due to the vast reach of aerodrome across the airfield and different airport layout plans, there are many variations possible for departure and arrival operations trajectory in the FoVs of the cameras. Hence, the miss-classification error decreases should all the defined variables are taken into account instead of only one of them.

The aircraft identification module comprises three sub-modules: aircraft tail number (region) detection, tail number recognition, and joint probability analysis. As discussed in the previous section, a deep neural network (DNN), named TextBoxes, is utilized to detect the tail number on an aircraft body in the image. Subsequently, the CRNN algorithm recognizes the detected texts in order to digitalize the tail numbers. Since there could be some other possible texts in the scene (Figure 11), non-tail number texts should be removed from the detections. One approach is to search over the detected aircraft bounding box in the image instead of the entire image. However, there would still be some unwanted detections (Figure 11, bottom). Moreover, the detected tail numbers at each video frame are not necessarily the correct tail number. In some cases, similarities between some characters result in erroneous recognition of some letters. Tail number occlusion by the aircraft wing and aircraft tilted pose while landing are the other possibilities.

Figure 11. Different detected texts scenarios in the cameras FoVs

Depending on the aircraft speed while operating during the camera observation period, 1 to 10 seconds take until it is out of FoV. This time leaves us with about 30 to 300 frames and tail number detections for each aircraft operation. Considering all these scenarios, the software is featurized with a joint probability analysis to find the most probable tail number for the operating aircraft. It jointly uses all of the recognized tail numbers during the observation of an operation and the FAA database. In the first step, all detected tail numbers are voted based on their maximum likelihood, which is estimated by the number of frames associated with their detection. An ICAO normative check (ICAO 1981, FAA, 2015) filters out the grammarly impossible tail numbers. The remaining tail numbers are then checked for the string similarities between the FAA database. A coefficient-based scoring system finds the score of the detected tail numbers based on their vote and their similarity score with the FAA database tail numbers. The aircraft is finally identified with the highest scored tail number.

Test Results

With the provided sufficient scene coverage from the designated distances, each camera layout independently places both departure and arrival operations under video surveillance. The collected data contains flight operations from various light aircraft types and various weather conditions (sunny, overcast, rainy, and snowy). Table 2 tabulated the camera layouts' flight operation mix during the data collection. During the observation in data collection time, the observed operations totaled 105 and 50 for camera layout 1 and camera layout 2, respectively (Table 2). As indicated in Table 3, camera layout 1 field of view had 97.1% accuracy regarding FoV selection in the airport environment for capturing the flight operations (i.e., departure operations and landing operations, including arrivals and touch-and-goes). Moreover, the software detected 98.1% of the captured flight operations in the video footage in layout 1. Similarly, the layout 2 system had 98% accuracy for both camera FoV selection and operation detection via our vision-based software.

Table 2. Camera layout operation mix during observation in data collection time

	Camera Layout 1			Camera Layout 2		
	# Observed Operations	# Captured by Cameras	# Detected by Software	# Observed Operations	# Captured by Cameras	# Detected by Software
Departure	34	33	32	28	28	28
Landing*	71	70	67+1**	23	23	22
Total	105	103	100	51	51	50

Note: * Landings: Arrivals + Touch-and-goes, **1: One departure operation is misclassified as a landing operation

Table 2 shows the AIVATS software performance is very high for the two operations count and operation status distinguishment tasks. From 154 operations captured by cameras, only three false-negative detections and one misclassification (i.e., false-positive) have resulted by using the software application.

Table 3. Accuracy of the operation count task during observation

System	Accuracy for Layout 1	Accuracy for Layout 2
Camera FoV selection	97.1%	100%
Software (automatic vision-based)	98.1%	98%
Camera + Software	95.2%	98%

Despite having a slight accuracy difference for operation count and operation status distinguishment compared to layout 1, layout 2 demonstrated higher potential for the task of aircraft tail number identification. Table 4 summarizes the two layout accuracies for the aircraft identification task. While the compiled software identified 64% of the total number of aircraft operations collected from layout 1 FoV, only about 14% of the identification errors stem from the software. On the other hand, layout 2 results indicate higher identification accuracy, and only 4% of the unidentified aircraft accounts for the software error. Closer range of view and lower aircraft speed in the operation time window of the FoV are the main reason for the increased identification accuracy in layout 2. Figure 12 and Figure 13 display the AIVATS software output displayed on the video footage screen (layouts 1 and 2) for further illustration.

Table 4. Aircraft operation identification (fleet mix) accuracy of the system

		Layout 1	Layout 2
% (correctly) identified		64%	82%
% unidentified	Aircraft with no printed tail number	7%	6%
	Not visible (small, cluttered, unclear tail numbers)	15%	8%
	Software error	14%	4%

Figure 12. AIVATS software performance during (top image) and right after (bottom image) the aircraft operation in layout 1

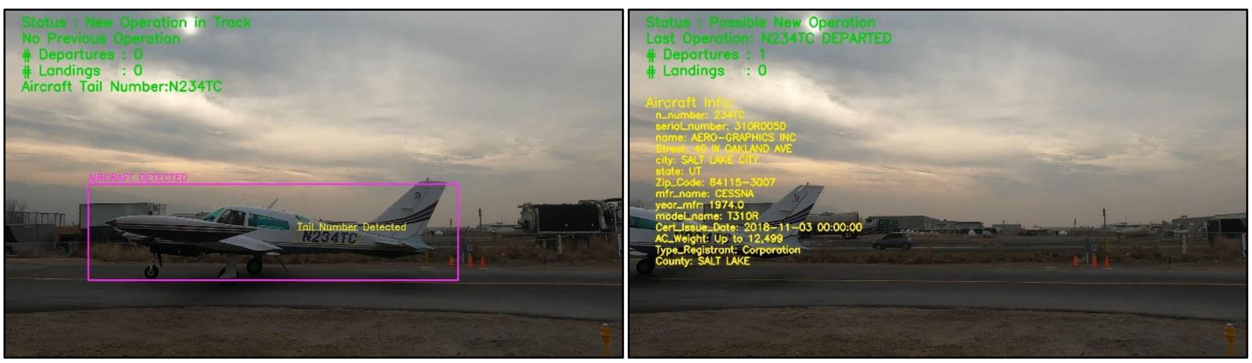

Figure 13. AIVATS software performance during (left image) and right after (right image) the aircraft operation in layout 2

Note: The computer codes (Python language) are available upon the request of the review committee members.

6.3. Hardware Configuration

6.3.1. Alpha Version

In the trial development stage of the system, the candidate camera for providing the required footage was a GoPro Hero 8 camera. The video footage is then processed off-line in the computer center on a Windows 10 64-bit Operating System with a 3.20 GHz Intel® Core(i7) CPU and 64.00 GB RAM. The following section presents the required hardware for having a stand-alone online system at airport sites.

6.3.2. Beta Version

This section is an introduction to the future work of the AIVATS for promoting the system. In this promotion, we aim to use single-board computers (SBCs) as the processor platform on the site. This approach makes it possible to have a low-cost stand-alone device for implementing the proposed system. Moreover, for a sustainable solution, a 5-watt solar panel power station can build the required charging infrastructure for such a system at airports. The complete package will include NVIDIA Jetson Nano 4GB Developer Kit, Waveshare Raspberry Pi HQ Camera with 12.3MP IMX477 Sensor, Adjustable Focal Length Industrial 8-50mm C-Mount Zoom Lens, and Waterproof Solar Panel PowerStation. Accordingly, the software will be adjusted for being embedded in the SBC platform.

7. Safety Risk Assessment

The probability and severity of an incident define that incident's risk level. FAA Advisory Circular 150/5200-37 (FAA, 2006) recommends the use of a safety matrix to evaluate existing risks in the design for the aviation area. The prepared Table 5 presents this report's risk matrix with four risk classes: low, medium, high, and very high. This table divides the probability and severity into five and four levels, respectively.

Table 5. Risk matrix

Probability Level	Severity Level			
	Negligible	Marginal	Critical	Catastrophic
Rare	Low	Low	Medium	Medium
Unlikely	Low	Medium	Medium	High
Possible	Low	Medium	High	Very high
Likely	Medium	High	High	Very high
Certain	High	High	Very high	Very high

As Table 6 illustrates, the video-based air traffic monitoring system does not pose any risk to airport operations. The risks associated with the system malfunction can also be prevented with the precautionary measures planed in the system design. Regular maintenance and troubleshooting keep the system operation safe. Table 6 discusses possible situations, their risk level, and the technical solutions.

Table 6. Potential risk cases

Case	**Probability Level**	**Severity Level**	**Risk Class**	**Solutions**
Algorithm problems	Unlikely	Negligible	Low	Technical support troubleshoots
Power outage	Rare	Negligible	Low	Regular maintenance
Camera platform displacement	Unlikely	Negligible	Low	Regular maintenance
Unsatisfactory maintenance	Rare	Negligible	Low	Maintenance staff training

8. Interaction with Airport Operators and Industry Experts

The team interacted with the following industry experts and airport operators, who contributed to the design process.

- Rod McDaniels - Innovations Program Manager - UDOT
- Jared Esselman - Director of UDOT Division of Aeronautics
- Paul Wheeler - UAS Program Manager
- Clint Harper - Aeronautics Business Development Manager
- Rich Stehmeier - Manager - St George Airport
- Martin Shupe - Aircraft Registration Program Manager - UDOT
- Matthew Swapp - Aeronautics Program Engineer
- Craig Ide - Aeronautics Engineer
- Habib Fathi - Co-Founder & Chief Science Officer at Pointivo

During the project time, six group meetings are actively conducted with the attendance of Rod McDaniels, Jared Esselman, Paul Wheeler, Clint Harper, Rich Stehmeier, Martin Shupe. The majority of the meetings were about 90 minutes long, and all of them took place through the Zoom platform. Also, the project lead had two separate meetings with the Utah Department of Transportation, Division of Aeronautics (Paul Wheeler, Clint Harper, Matthew Swapp, and Craig Ide). From the beginning of the project, different aspects of the design were regularly/actively discussed and checked with the mentioned groups. A few of the important notes from these meetings are as follows.

Rich Stehmeier provided insights on current aircraft operation tracking methodologies. He encouraged us to research how RCC, GARD, and ADS-B work. He also suggested having a variety of aircraft and airport types during the collection of the video data. As for the preliminary data collection, Jared Esselman suggested five airports, namely, Bountiful Airport, Heber Valley Airport, Brigham City Municipal Airport, Spanish Fork Airport, and Logan-Cache Airport, for having a good mix of aircraft types (jet, prop, etc.). Jared emphasized the use of low-cost equipment for the project in order to help a vaster range of airports, possibly all non-towered public-use airports.

After the first two meetings with Paul, Clint, Matthew, and Craig, an airport visit is conducted to check the camera placements in the field as well. Bountiful Airport is used for the first airport visit. During the visit, the project lead had a thorough discussion with Craig and Matthew about the camera distances from the runway centerline and connector ends. Matthew highlighted the importance of paying attention to the airport layout plans during the design process. Clint emphasized the use of a traffic sheet during future data collections for comparing it with the captured flight operations via camera systems and the software. The airport visit (Figure 14) was conducted with prior coordination with Steve Durtschi (Bountiful Airport manager). Similarly, the other airport visits were conducted under airport manager supervisions and approvals (i.e., Cris Child (Spanish Fork Airport manager) and Tyler Pugsley (Brigham City Municipal Airport manager)).

Figure 14. Team Skypark airport visit

Martin Shupe said that a dream system would be able to associate captured tail numbers back to published FAA registration information. Aside from aircraft identification significance, his other priority for the design of a video-based air traffic surveillance system was landing fee data association. This could automate the landing fee-charging process and save some time for the airport operators. With regard to software development, Rod McDaniels emphasized the use of sufficient hardware to prevent data congestion while recording the air traffic data.

To evaluate the practicality of the design for marketing, we had a meeting with Dr. Fathi, who has a successful experience in running a startup AI (Artificial Intelligence) company. This meeting was essential since our design is also AI-based. Dr. Fathi received his Ph.D. title in Computer Vision / Civil Engineering from the Georgia Institute of Technology and was a co-founder at Pointivo. Pointivo's analytics platform is built by a team of AI and computer vision software for physical asset inspection. During our meeting with Dr. Fathi, he approved the technical approach used in the project and suggested the team develop the aspect of which problems we are solving with this technology, the value of the potential product, and the potential target customers.

He said that the applicability of such a system depends on the user's need and their restrictions. As a result, he strongly encouraged us to be in touch with airport operators and managers. In this way, the design process proceeds while considering the restrictions that existed in the airports as well.

He also provided insights on how to develop a cost analysis for the project, in which we would have a couple of options. The first recommended option was to consider the costs for installation, maintenance fee, power, and administrative costs. The second suggested option was to license the technology to the airports so that each facility would be responsible for the costs associated with it.

9. Cost-Benefit Assessment

In this section, the practicality of the AIVATS implementation is assessed by analyzing the weight of system cost versus the system benefits. The discussed case study in the system section is used for the cost estimation. Bountiful Airport, Brigham City Municipal Airport, and Spanish Fork Airport were the field test locations in the alpha stage of the system implementation. The system's total cost can be divided into design/field tests and operation costs. The framework design/field test expenses are enumerated for two research and development stages: alpha and beta. The alpha covers the project time spent preparing the proposal submittal along with its necessary materials (e.g., design description, computer codes, preliminary field tests, etc.). In the beta, the product prototype cost is then evaluated for marketing purposes. Table 7 and Table 8 tabulated the detailed alpha and beta stage costs, including labor, travel, and material fees.

Table 7. Research and development cost – alpha phase

Item	**Rate**	**Quantity**	**Subtotal**	**Remarks**
Labor - University Design Competition				
Student Efforts	$25/hr	360 hrs.	9,000	1 grad student – 300 hrs 2 undergrad students – 30 hrs ea.
Expenses				
Travel	$0.54/mil	304 mil	$165	Airports visits
Miscellaneous	$800	Lump-Sum	$800	Hardware (cameras and tripods)
Subtotal			$9,965	

Note: This table is inspired by Guidance for Preparing Benefit/Cost Analysis (Byers, 2016)

As tables demonstrate, labor is required from undergrad and grad students as well as technician and computer engineers to maintain the system operable. The different amounts of material needed in layout 1 and layout 2 design of the AIVATS affect the total cost per unit. The estimation for preparing 100 units of AIVATS layout 1 and layout 2 totaled $74,400 and $130,800, respectively.

Table 8. Research and development cost – beta phase

Item	**Rate**	**Quantity**	**Subtotal**		**Remarks**
Labor - University Design Competition					
Student Efforts	$25/hr	720	18,000		1 grad student
Expenses (materials for **one unit**)					
			Layout 1	Layout 2	
NVIDIA Jetson Nano 4GB Developer Kit	$108	2 to 4*	$216	$432	Hardware
Raspberry Pi HQ Camera with 12.3MP IMX477 Sensor	$84	2 to 4*	$168	$336	Hardware
Adjustable Focal Length Industrial 8-50mm C-Mount Zoom Lens	$50	2 to 4*	$100	$200	Hardware
Waterproof Solar Panel PowerStation	$40	2 to 4*	$80	$160	Hardware
Subtotal			$74,400	$130,800	For 100 units

Note: This table is inspired by Guidance for Preparing Benefit/Cost Analysis (Byers, 2016)

*Depending on the number of required units for layout 2

With the completed system development stages, AIVATS system operation requires an installation plan and regular maintenance. A monthly troubleshooting plan is considered to conduct the service. Table 9 represents the associated costs of system operation over an operational period of 10 years.

Table 9. System operation costs

Item	**Rate**	**Quantity**	**Subtotal**	**Remarks**
Labor for installation				
Electrician	$50/hr	8 hrs.	$400	1 worker
Computer Engineer	$50/hr	8 hrs.	$400	1 worker
Labor for maintenance				
Technical Support	$100/day	120 days	$12,000	Once per months
Subtotal			$12,800	Per unit for 10 years

The proposed video-based system provides the airport industry with aircraft operation count, fleet mix information, and spatial awareness in the aerodrome of the airport. The aircraft operation count supports future federal and state planning and funding allocations. The fleet mix information is especially vital for estimating the environmental impacts of the airport on the local community. This information includes operating aircraft type, model, engine model, which will be further used as a basis for estimating pollutant and noise emissions. In order to estimate the weight of the proposed system's benefits, the alternative methods are assessed for providing the operation count and fleet mix information. Sound-level acoustic counters are used as an alternative for operation count. Since these acoustic counters deliver only countings and not aircraft identification, an airport operator who is also responsible for charging landing fees is used as a resource for providing the fleet mix information at the airport. It should be noted that only a small number of airports, mostly towered airports, have such an employee resource, and non-towered airports miss such valuable data collection. Table 10 shows that both AIVATS layouts benefit outweighs the cost with a ratio of more than 3.

As a side note, neither of the alternative methods is as accurate as the proposed system. The proposed system promises higher operation counting accuracy compared to the acoustic counters. There is no alternative with the same or higher level of accuracy provided by AIVATS. Therefore, it can be easily claimed that the benefit to cost ratio is much higher than the calculated one in Table 10. However, the acoustic counter gave us a good understanding of estimating the cost of flight operation count at non-towered airports. Similarly, while AIVATS can provide the fleet mix information for all flight operation types, landing fee data delivered by the airport operator does not contain fleet mix information of departure and touch-and-go operations. Nevertheless, it is used to estimate the minimum cost of this service. The increased aircraft counting and fleet mix information accuracy will lead to more accurate future state and federal environmental planning and funding allocations, thereby increasing the potential benefit-to-cost ratio.

It is noteworthy that the system's spatial awareness might prevent a runway incursion and an accident, which adds to the system values. For instance, preventing one aircraft damage could save about $230,000 (FAA, for typical GA aircraft). However, this cost-saving is not reflected in the calculated benefit-to-cost ratio. Otherwise, the calculated ratio could be even higher than what it is now.

Table 10. Cost Summary

Item	**Unit**	**Qty**	**Subtotal**	**Remarks**
Costs				
System with layout 1 Development	$744	1 period	$744	Table 8
System with layout 2 Development	$1,308	1 period	$1,308	Table 8
Installation & maintenance	$1,280	10 yrs.	$12,800	Table 9
Total Cost	System with layout 1		$13,544	Total 10 year cost per unit
	System with layout 2		$14,108	
Cost prevented (benefits)				
Operation count	$4,800[1]	3	$14,400	Using a sound-level acoustic counter and assuming three units are needed[2]
Fleet mix information (associated with landing fee charges)	$56,000	0.5 labor/yr.	$28,000	Assuming that the job is done with engaging only half of a worker workday
Accident Cost Prevented			TBD	This value is added because of the increased spatial awareness in aerodrome (especially runway) for operators. However, it is not reflected in the calculated benefit to cost ratio
Total Benefit			>$42,400	The benefit is more than $42,400 due to AIVATS's promoting spatial awareness
Benefit to Cost Ratio	System with layout 1		3.13	**Benefit outweighs cost[3]**
	System with layout 2		3.01	

Notes:
[1] ACRP report 129
[2] Multiple counters are needed for longer runways; 92% using three counters on single 5,500 ft. runway.
[3] Operation count accuracy that our proposed system (AIVATS) promises is more than 95% (error<5%) and much higher than the acoustic counter, which has an error of 5%-99% (ACRP report 129). It should also be noted that the acoustic counters do not provide fleet mix information while AIVATS provides it with 64% and 82% accuracy using layout1 and layout 2, respectively

10. Projected Impact of Design

10.1. How This Project Meets ACRP Goals

The automatic aircraft monitoring system proposed counts the operations in non-towered airports and automatically identifies aircraft operations, supplying the airport managers with valued information about the airport traffic. It facilitates the coordination of runway (pavement) maintenance to improve airport operations (ACRP Guidelines, 2020-2021).

Participating in this competition raised the teams' awareness of current airport problems. By developing research and talking with industry and airport professionals, the team was able to recognize the wide range of problems that could be solved. There are many career opportunities available in the aviation and airport area that the team has not previously considered. This awareness would not have been raised without the obligated meetings with the aviation operators and experts (ACRP Guideline, 2020-2021).

10.2. Commercial Potential

As discussed in the cost-benefit assessment section, the benefits of the proposed system outweigh its cost. On the other hand, the product of the design can be beneficial for aviation authorities to keep records of the local airports' activities under their jurisdiction. The other potential customer would be airport managers who charge landing operations in their airport. Moreover, implementation of our design will be an easy process, which makes it even more desirable for the marketing aspect of the project. In addition, the system will be easy to implement and use at any non-towered airport with any airport layout plan. No limitation on the airport layout plan is on the use of the proposed design. More than 20,000 non-towered airports across the U.S., and the AIVATS system is applicable for these specific airports.

10.3. Impacts

The proposed system provides non-towered airports with flight operation count, flight status (departure/arrival), and fleet mix information. All other existing methods rely on either the sound of aircraft (acoustic counter) or an external auxiliary unit mounted on aircraft (ADS-B out). The former is only able to count the number of operations with no further details; moreover, their counting accuracy is very low, with errors between 5%-99% (ACRP report 129). The latter, as discussed, rely on ADS-B out; nonetheless, the aviation fleet equipage rate with ADS-B out units is still low (FAA current equipage levels, 2021), leading to inaccurate measurements. On the other hand, the proposed system independently gives an accurate tool to decision-makers in the aviation industry to accurately collect their detailed air traffic data in the airports. This data will be essential for future airport improvement plans, including operational, financial, and environmental. Runway safety improvement will be another intangible impact of this system by providing operators with visual clearance of the runway's two ends.

Appendix A: Contact Information

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Appendix B: Description of the University

The University of Utah is a public research university, founded in 1850 and located in Salt Lake City, Utah. Its mission is to "fosters student success by preparing students from diverse backgrounds for lives of impact as leaders and citizens. We generate and share new knowledge, discoveries, and innovations, and we engage local and global communities to promote education, health, and quality of life. These contributions, in addition to responsible stewardship of our intellectual, physical, and financial resources, ensure the long-term success and viability of the institution". As core values, the University of Utah focuses on student success and engagement, research and teaching excellence, diversity, sustainability, global vision and strategy, community, and leadership.

The University of Utah is committed to excellence, innovation, and diversity in conducting transformative, high-quality research. Recognized as a Top-Tier 1 research university (Carnegie Classification of Institutions in Higher Education) – the U continues to develop groundbreaking research on a local, national, and international level. The university's distinguished research community is cultivated through its 18 colleges, 35 interdisciplinary programs, 100 academic departments/divisions, and 120 centers/bureaus on campus.

It counts with more than 963 thousand square feet for research space on campus, and received $602 million in research funding during 2020, contributing to students development and community growth and innovation. The University of Utah will continue to develop cutting-edge research to enhance the lives of current and future generations to come.

Appendix C: Description of Non-University Partners

Not Applicable.

Appendix D: Design Submission Form

See attached page.

Appendix E: Evaluation of Educational Experience Provided by the Project

Students (All team members discussed the answer)

1. Did the Airport Cooperative Research Program (ACRP) University Design Competition for Addressing Airports Needs provide a meaningful learning experience for you? Why or why not?

Yes, absolutely! The design process for the proposal submittal of this project had all the elements that are both essential for real-world work and absent in academic education. A roundabout design process taught us to consider every aspect of a design than only the technical part. Risk and cost-benefit assessments are two of those aspects. Moreover, the interaction obligation made us talk to the people who really are dealing with the challenge we were trying to solve. Our design would not have been got to this stage if we had not discussed the issues with the airport operators and industry experts. And the last but not the least meaningful learning experience for our team is teamwork. During the project time, there were several obstacles that we only were able to overcome as a team.

2. What challenges did you and/or your team encounter in undertaking the competition? How did you overcome them?

There were a few challenges during the completion of the design process. The major one was working during the pandemic COVID-19. The pandemic hindered us from having in-person meetings with advisors as a team, and we had to conduct our weekly meetings virtually. The nature of our design process required conducting several in-field data collections at airports. As a result, we had to wait for university permission before starting our data collections. Nevertheless, the team could finish the project on time, at the same time following all federal and state guidance issued for the pandemic.

3. Describe the process you and your team used for developing your hypothesis.

AIVATS's design idea started with the project lead experience in his internship in the aviation industry. He managed the student team by assigning tasks to the team members. Before the task assignment, all team members had a complete introduction session, and the project tasks are assigned accordingly. We started with biweekly meetings from the start of the project with advisors and brainstormed as a team for every challenge we faced. The first month of the design process was allocated to the literature review in order to find the gap of the selected topic. As the reference section illustrates, several ACRP reports, journal papers, conference proceedings, and relevant websites are dug through by the team members. The review process kept on during the project completion. However, the main efforts after the first month were put towards data collections and interviews. With having enough material at this time, the project lead was responsible for the computer codes part of the design, and other team members conducted the coordination for meeting and interview with industry expert and airport operators. Once the results of the software were ready, the team started weekly meetings to prepare the manuscript body of the design proposal. The whole process would not have been accomplished without the advisors' supervision and insight during the project time. They were always supportive, insightful, and initiative to tackle the challenges.

4. Was participation by industry in the project appropriate, meaningful and useful? Why or why not?

Yes, absolutely! First, the industry experts we interacted with gave us insight into proceeding with the design for a potential practical product. Many technical aspects of the design are inspired by interaction with experts and their novel ideas. For instance, the camera placement was engineered with the experts' consultation. Second, having experience in running real-world companies, the experts showed us the correct approach in developing the design cost-benefit assessment. The detailed cost-benefit section provided in this proposal reflects the meaningful interaction with the experts in this area.

5.What did you learn? Did this project help you with skills and knowledge you need to be successful for entry in the workforce or to pursue further study? Why or why not?

We all agree that the most take on of all team members was the teamwork experience. After that, an academic and practical approach toward a design process is the second lesson learned of the team members. The process involved the team members with academic writing tasks as well as having a statistical problem-solving view. Not only did this project help us with skills and knowledge we need to be successful for entry in the workforce, it also provided us with many useful connections that we can pursue to find both a decent academic position and job.

Faculty

1. Describe the value of the educational experience for your student(s) participating in this competition submission.

The team consisted of three students from different cultural backgrounds. It was a great opportunity for them to overcome communication barriers, especially with the industry and aviation experts. This project built a potential bridge from their education to their possible future job in the aviation industry. Also, both graduate and undergraduate students were engaged in the completion of the design. Therefore, the other aspect of the project value for students is enhancing teamwork skills in a team with different knowledge levels.

2. Was the learning experience appropriate to the course level or context in which the competition was undertaken?

Yes. Also the time allocated to the project helped the team members to overcome their knowledge gaps to meet the proposed design requirements.

3. What challenges did the students face and overcome?

The biggest challenge was starting the project in the middle of a pandemic. However, the individual hard work and their teamwork were the keys to finishing the project on time and successfully.

4. Would you use this competition as an educational vehicle in the future? Why or why not?

Yes. The research promising results can assist the faculty in developing the learning modules in the following courses: BIM (Building Information Modeling), Advanced Computer-Aided Construction, and Quantitative Methods in Transportation Operations. Furthermore, the advisors will maintain the relationship with the airport personnel and conduct airport visits as part of their coursework material. It will engage the students with the airport industry in our school.

5. Are there changes to the competition that you would suggest for future years?

Not at this time.

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