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IMAGE PROCESSING AND MACHINE LEARNING TECHNIQUES FOR AUTOMATED DETECTION OF PLANES AT UTAH AIRPORTS

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RESEARCH

UDOT Keeping Utah Moving

Utah Department of Transportation - Research Division
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16. Abstract

Most of the airports in the United States are non-towered airports. Utah is not an exception to this rule. As a result, these airports fall behind in terms of aircraft operation count and identification. On the other hand, image detection and recognition have long been assisting different industrial areas in shifting towards automation in performing numerous tasks. That said, this work attempts to utilize various image processing and machine learning techniques to automatically detect and count the airplanes in operation at the Utah airports.

The first major task to accomplish such an automatic system is data collection. Data collection will be divided into office and in-field data collections. The office data collection aims to build a bridge from identified aircraft at the airports to FAA-registered aircraft data. Also, a great amount of in-field data collection is needed first to find a solution for an optimal camera deployment at airports and second to create a data repository of different aircraft transported through the airports. This data includes aircraft trajectory while in operation on or near the airport runway environment as well as the image data captured from the operating aircraft. The former helps us detect the strategic airfield placement for camera deployments for accurate aircraft operation detection. The latter is required for feeding the machine learning computer packages as training data.

Data processing is the second major task and structures the software development of the project. This task comprises several required subtasks before finalizing an aircraft operation count and identification. These subtasks include but are not limited to establishing vision-based algorithms for motion detection, aircraft detection, operation tracking, aircraft trajectory quantification, tail number region detection, tail number character recognition, and aircraft operation identification. This report also comprehensively reviews the computer vision methods tested to accomplish the above-mentioned subtasks.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

UNIT CONVERSION FACTORS

NO UNIT CONVERSIONS

LIST OF ACRONYMS

ATC	Air Traffic Control
FPS	Frames Per Second
UDOT	Utah Department of Transportation
FOV	Field of View
YOLO	You Only Look Once
SSD	Single Shot Detector
GARD	General Audio Recording Device
RCC	Radio Click Counting
ADS–B	Automatic Dependent Surveillance-Broadcast
MOSSE	Minimum Output Sum of Squared Error
JPA	Joint Probability Analysis
S/TC	Security/Trail Camera

EXECUTIVE SUMMARY

The Aeronautics Division of the Utah Department of Transportation (UDOT) sponsored this project to help non-towered airports automate aircraft operation count and identification. A video-based air traffic surveillance system is developed to keep records of the flight operations and their status at Utah airports. There are 46 public-use airports in Utah. The technical advisory committee (TAC) selected five Utah airports for the project field test locations collected at: 1) Bountiful, 2) Heber, 3) Logan, 4) Brigham, and 5) Spanish Fork.

Air traffic data is collected from the airport test locations at different times of the day and in different weather conditions, including sunny, cloudy, rainy, and snowy. A GoPro Hero 8, GoPro Hero 3, and Fuji Film XT-30 mounted on steel tripods are used to record the necessary video data. After preliminary discussions, two camera layouts are set to test for the camera deployments in the airports. Layout 1 targets the runway area, and layout 2 captures the footage of the taxiway-runway connectors. The motivation for the second layout is to obtain a closer view of aircraft operations for possibly higher identification confidence. Several data collections are conducted in the above-mentioned test location for each camera layout separately, and the results showed a high accuracy regarding the flight operation coverage for both camera layouts.

To empower the camera sensors with computer vision, the research team developed a machine learning-based software. After transmitting the video data to the computer center, the software processes individual video frames to detect, count, and identify any operating aircraft in the airport aerodrome. The software backend is compiled first in MATLAB language and then is ported to Python language for a better inference time. Several machine/deep learning algorithms are used for several tasks such as motion detection, aircraft detection, operation tracking, aircraft trajectory quantification, tail number region detection, tail number character recognition, and aircraft operation identification. This report provides detailed descriptions of each of the implemented algorithms that are included in the final computer vision system. The results show a promising accuracy regarding the operation count. As long as the tail numbers printed on the body of the aircraft follow a conventional format (e.g., size, orientation, font, color, and design), the software can successfully identify the target aircraft.

1.0 INTRODUCTION

1.1 Introduction

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 operation counting 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 emit different levels 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.

Several attempts have been made to address the operation counts at airports. Of them, acoustic, radio, radar, and satellite-based methods are the most common. However, these methods have drawbacks in terms of accuracy, feasibility, and cost. On the other hand, a vision-based method can solve these problems and has been the central core of this research methodology. In recent years, machine vision techniques proved to be a practical solution for similar transportation applications such as transportation asset inventorying (Cross et al., 2020 and Farhadmanesh et al., 2021a, and Farhadmanesh et al., 2021b). The following describes the current problem with the existing methods for counting and recognizing the airport operations at non-towered airports.

1.2 Problem Statement

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's identity, nor is it able to provide a real-time assessment of the airport runway to guarantee the operation's (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 the aircraft, and some outages are expected due to poor GPS geometry when satellites are out of service (Koh, 2019).

That said, our proposed system aims to provide 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 research, our automatic independent video-based air traffic surveillance system (AIVATS) has a solution for all airport types (with centralized and decentralized terminals).

Cameras at strategic locations at the host airport are the required hardware of this video-based air traffic surveillance solution (Figure 1). The designed software empowers the cameras 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 camera 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).

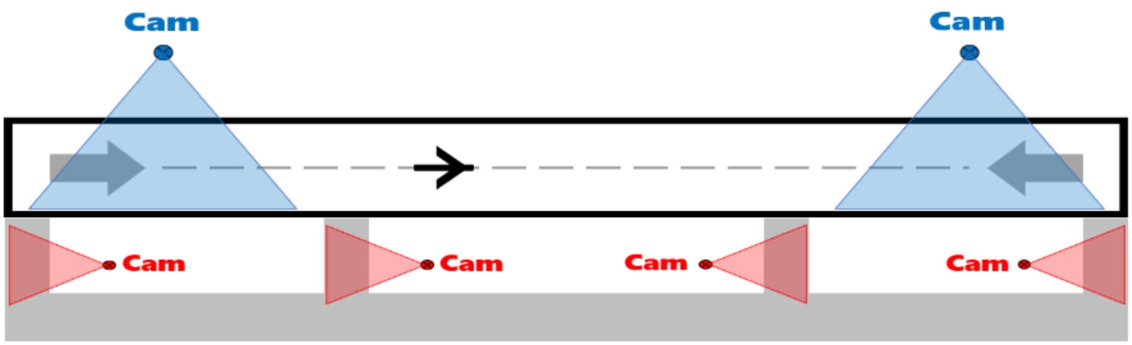

Figure 1 Camera layout 1 (blue colored), and layout 2 (red colored) in the airport

1.3 Background

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 since 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.

1.3.1 Non-Vision-Based Systems

The ADS-B system determines the aircraft's 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 only the data from the aircraft's navigation system (FAA, 2019). 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).

On the other hand, the GARD system monitors 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.

1.3.1 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 control towers at 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 tower 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 report presents an independent vision system to monitor aircraft operations in the airport environment. It 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 connector towards the runway so that arrivals and departures can be captured from the runway's 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 detected operation 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 can accurately count the number of operations. The test results are assessed in the data evaluation section. 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 research methods 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.

1.4 Objectives

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 the camera layout plans subsection in the research method section. 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. The outcome data is useful for airport owners, managers, pilots (airport users), and basically, everyone involved with airport operations.

1.5 Outline of Report

- Introduction
- Research Methods
- Data Collection
- Data Evaluation
- Conclusions

2.0 RESEARCH METHODS

In this section, the algorithms required for the proposed system are first evaluated. We explain how they are selected and why. In this process, the collected preliminary data is used as a basis in order to have compatible software to the actual video footage of the final system. Later, Section 2.2 discusses the camera placements and provides a field of view for maximizing aircraft operation capture by the proposed camera systems. Finally, we elaborate upon the software backend regarding the computer vision modules that actually empower the recorded video footage with aircraft operation recognition feature.

2.1 Algorithm Selection

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 systems.

2.1.1 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.

2.1.2 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.

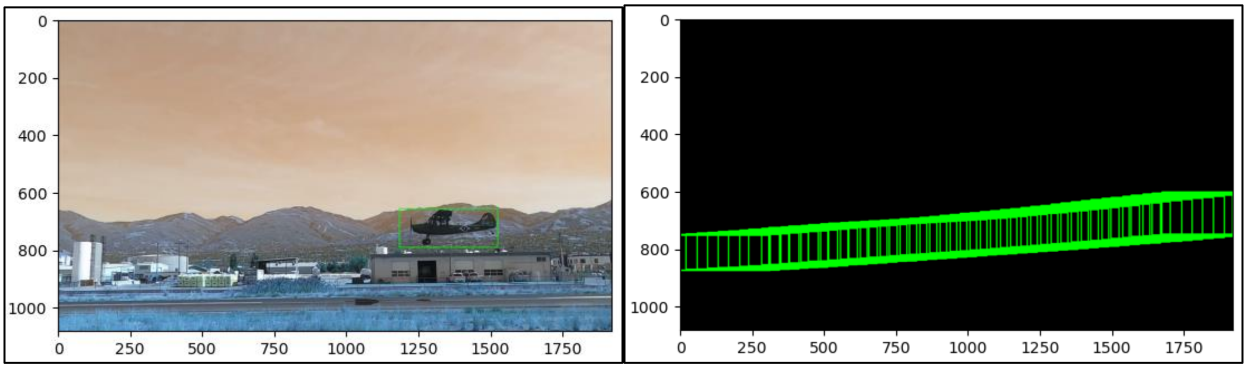

Figure 3 Left: Detecting aircraft in a video frame, Right: Tracking the detected aircraft in the consecutive video frames

2.1.3 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 resulting 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 proceeds 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 on 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) and the EAST algorithms are tested, and the former is selected for its accurate and fast detection. The Convolutional Recurrent Neural Network (CRNN)

(Shi et al., 2016) and Tesseract (an open-source OCR library) are tested, and CRNN is selected for being used as the backend of the software's tail number recognition module. These two networks (TextBoxes and CRNN) 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.

2.2 Camera Layout Plans

After careful observation of the various existing airport layout plans and interaction with local airport operators, two possible camera layouts for 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 as shown in Figure 5 (bottom right), 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).

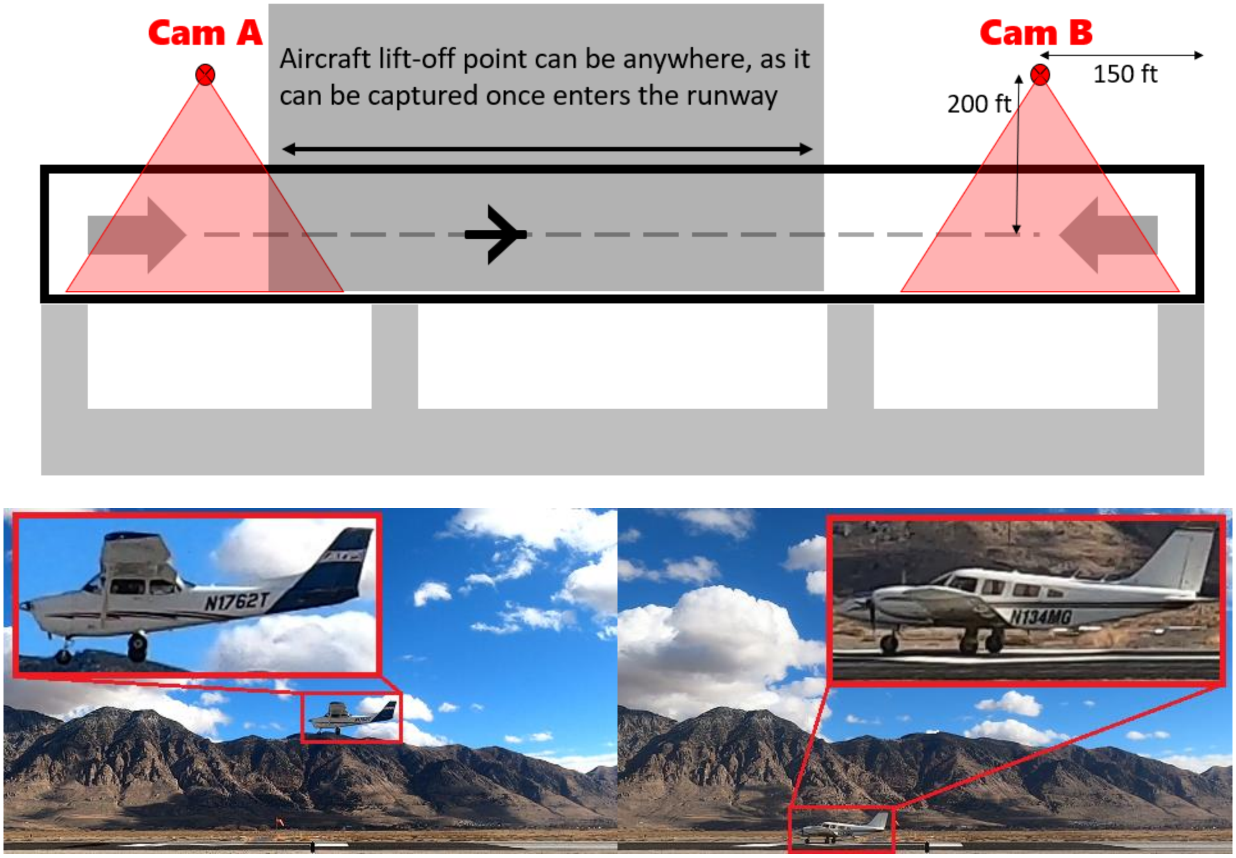

Figure 5 Top: Camera deployment in layout 1, Bottom: Field of view in Camera A for an arrival operation (left) and a departure operation (right) on the runway area

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 are able to distinguish them based on the aircraft motion direction in the respective connector.

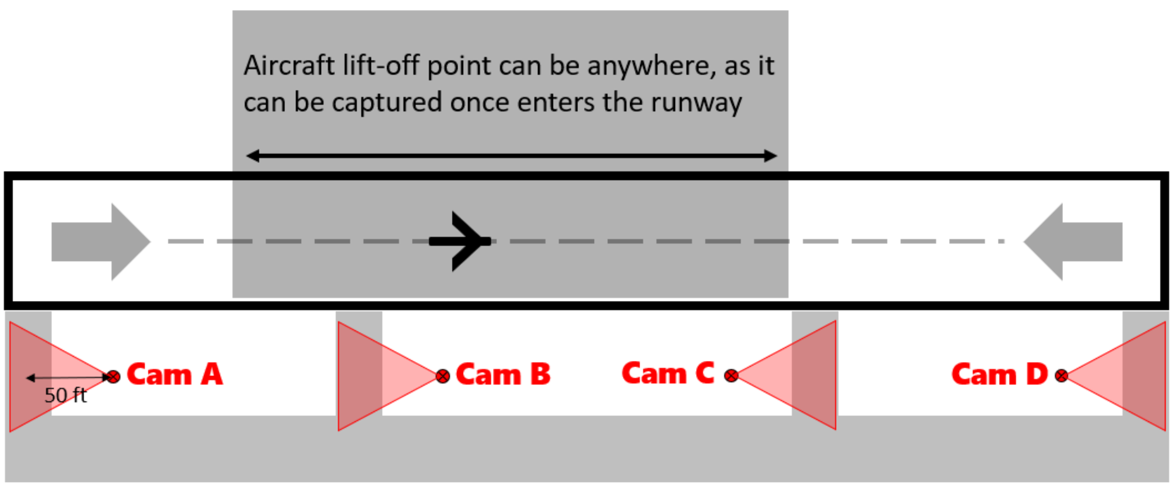

Figure 7 Top: Camera deployment in layout 2, Bottom: Field of view in Camera A for a departure operation (left) and an arrival operation (right) on the taxiway-runway connector area

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 five public-use airports in Utah: Bountiful Airport, Brigham City Municipal Airport, Spanish Fork Airport, Heber City Airport, and Logan-Cache Airport. In the best-experimented setting, the dataset was collected with low-priced commercial off-the-shelf cameras (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. The data collection section discusses the different video resolutions that are tested for different tasks (i.e., aircraft operation count and identification).

Figure 9 GoPro Hero 8 camera setup

Other than testing different video resolutions, the project lead examined the effect of using an IR cut lens. This was done originally to improve system accuracy regarding tail number recognition, especially in camera layout 1 that has a longer range of view. Using an IR cut lens (Figure 10a) can help us in cases of extreme illumination conditions. These lenses work by being formulated to record infrared light particles. At not-so-extreme conditions, they do not make any difference (Figures 10b and 10c). However, when the sun was shining straight to the camera lens, there was a difference, and the tail number is more apparent after using the IR lens. Therefore, the accuracy of recognitions will be increased depending on the illumination conditions.

a

b

c

d

e f

Figure 10 Effect of the IR cut lens (a) at not-so-extreme illumination conditions (c and d) and at extreme illumination conditions (e and f); b) camera without IR lens

lens

2.3 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 in 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 11 illustrates the software backend flowchart from the video feed to the flight status recognition and aircraft operation identification.

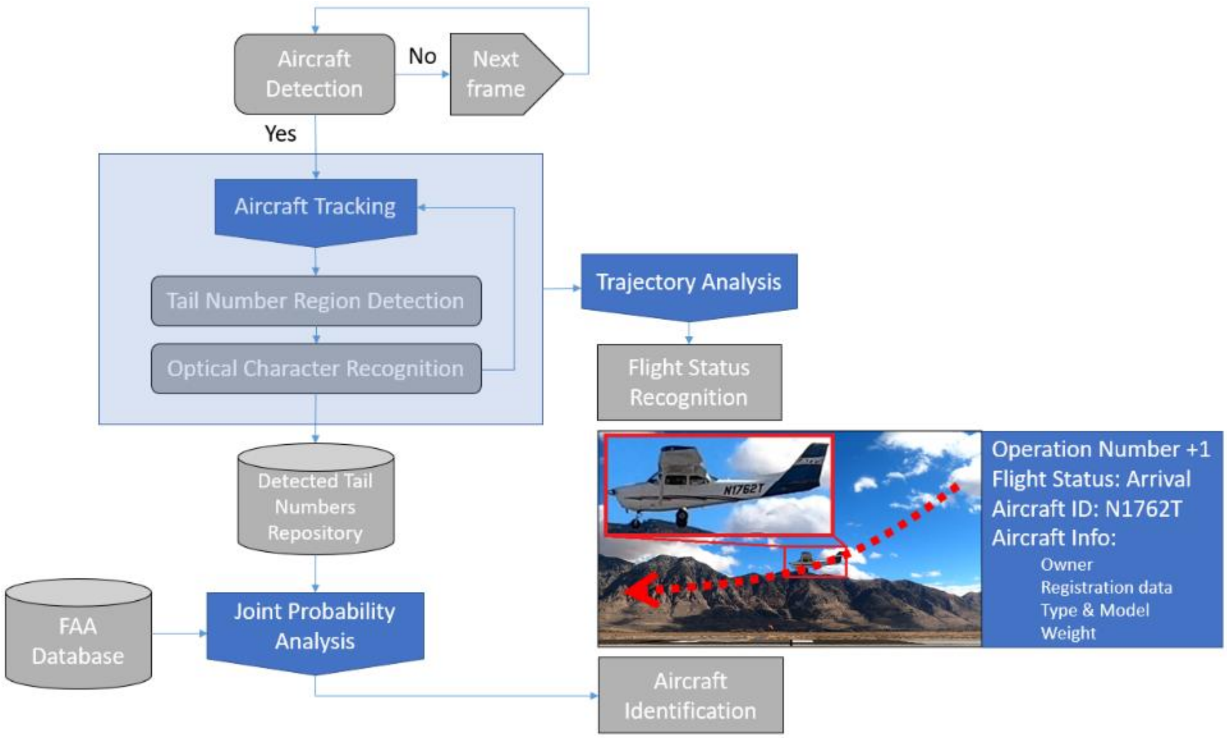

Figure 11 Software flowchart

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. The 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 benefit 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 trajectories in the FoVs of the cameras. Hence, the misclassification error decreases if 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 12, 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 12 Different detected texts scenarios in the cameras' FoVs

Depending on aircraft speed while operating during the camera observation period, it takes from 1 to 10 seconds 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 featured with a joint probability analysis (JPA) 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 grammatically 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. Figure 13 illustrates the identification process with one example. This solution is called the JPA solution 1.

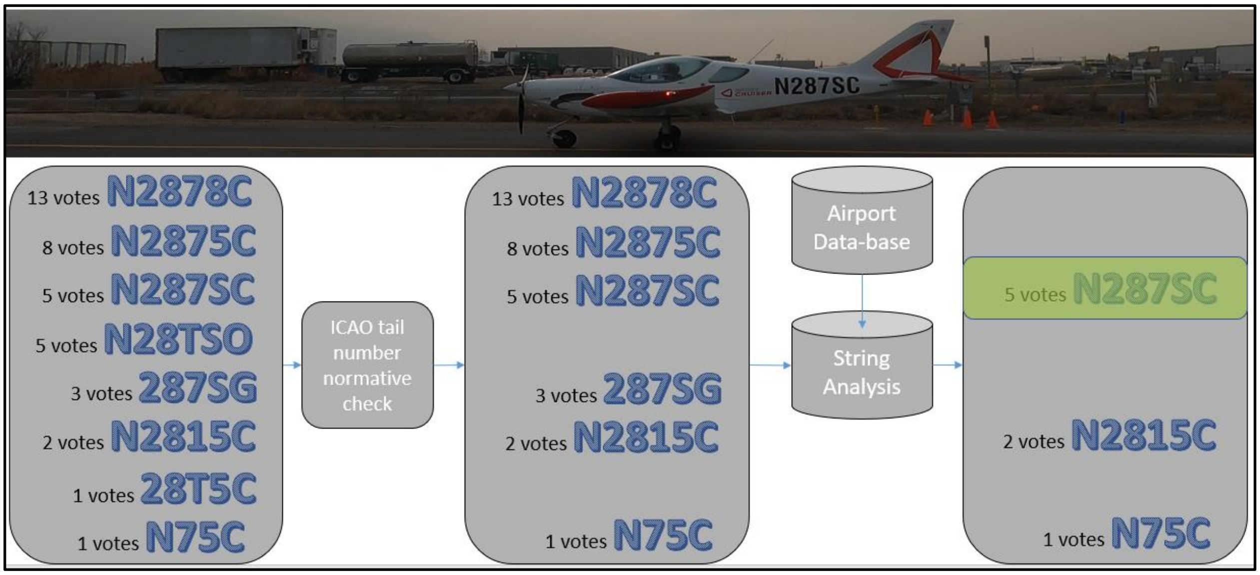

Figure 13 Aircraft identification steps

As described in the previous section (camera layout plans), camera layout 1 FoVs pose greater challenges regarding the aircraft tail number recognition task. This stems from the longer range of view and the fact that the operating aircraft are at a much higher speed compared to camera layout 1. That said, it is possible that neither of the recognition attempts results in the actual tail number. As a result, the JPA solution 1 cannot identify the aircraft's identity. Two schemes have been devised to overcome these challenges and increase the accuracy of the camera layout 1 for aircraft identification. First, a bilateral filter is applied to the detected aircraft image. Second, JPA solution 2 helps us find the closest tail number in the registration database.

A bilateral filter (Figure 14) is a non-linear, edge-preserving, and noise-reducing smoothing filter for images. It replaces the intensity of each pixel with a weighted average of intensity values from nearby pixels. This weight can be based on Gaussian distribution and depends not only on the Euclidean distance of pixels (which is preserved with the spatial kernel) but also on the radiometric differences (like color intensity). This preserves sharp edges in the image.

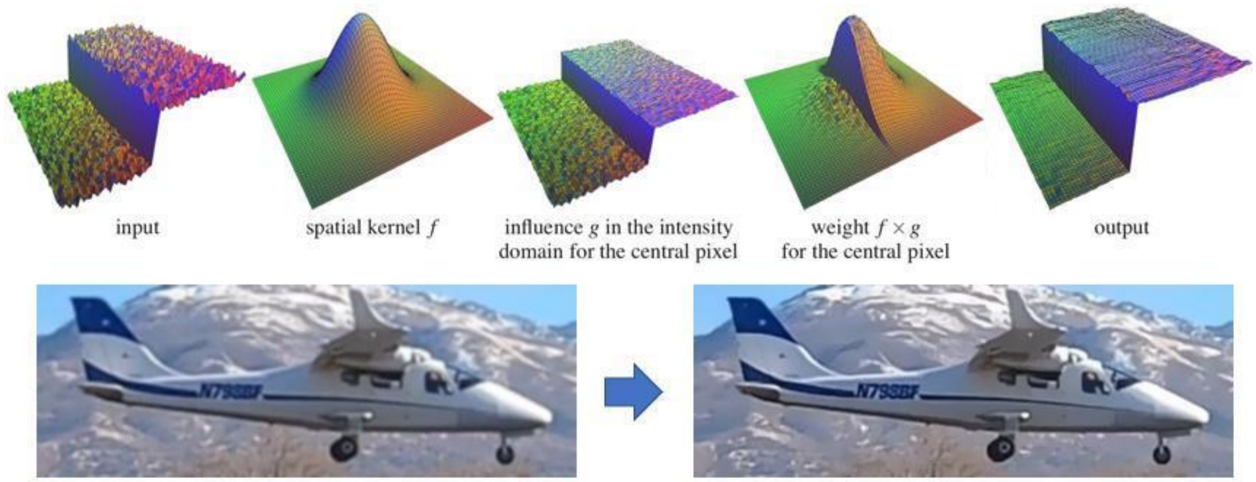

Figure 14 Bilateral filter and the edge-preserving effect on blurry images taken from aircraft in operation using cameras at camera layout 1

As Figure 15 shows, JPA solution 2 assesses each of the recognized characters individually. It should be noted that each recognition is not an absolute deterministic recognition but actually a representation of a probability distribution. For example, in this recognition task in Figure 15, each letter has a probability distribution (e.g., "N" is detected with 68% confidence). As a result, each recognized letter could be another character (e.g., the first letter could be M with 18% confidence). JPA solution 2 uses these confidences jointly with the FAA registration database to solve the maximum likelihood equations (Figure 15), which gives the finalized recognition result. It is noteworthy that the software only uses the JPA solution 2 in cases when the JPA solution 1 cannot identify the aircraft tail number.

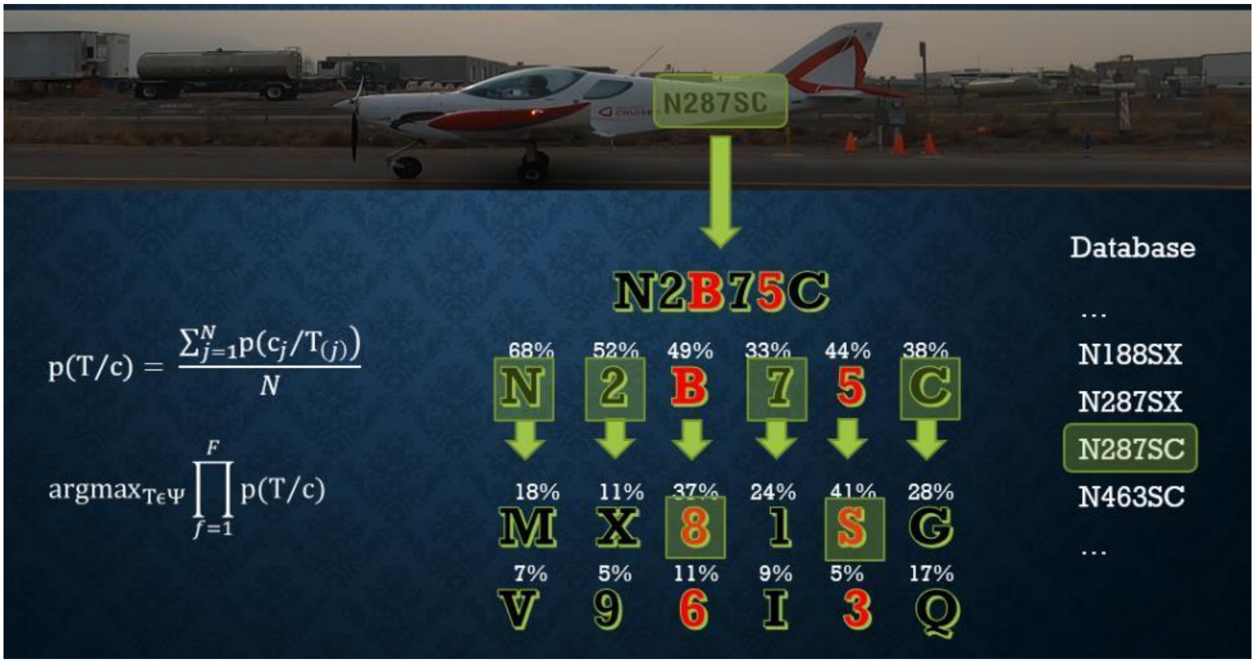

Figure 15 JPA solution 2

2.4 Summary

In developing the software, we first evaluated the challenges that are common in an airport environment. Two camera layouts are devised to test both long-range (layout 1) and close-range (layout 2) settings. Subsequently, an extensive review of the previous methods is done, and the best algorithms are selected for use in the backend of the defined modules. The core software modules include aircraft detection, aircraft tracking, tail number region detection, tail number recognition, and joint probability analysis.

3.0 DATA COLLECTION

3.1 Overview

Several data collections have been conducted to find the best setting for video recording configuration as well as the placement of the cameras in the two defined layouts in the previous section. Furthermore, the collected data is used as a basis to evaluate system performance regarding accuracy and feasibility. The test locations are five public-use airports in Utah:

1. Bountiful Airport
2. Brigham City Municipal Airport
3. Spanish Fork Airport
4. Heber City Airport
5. Logan-Cache Airport

The figures below show the test location airports and their configuration (layouts). The figure order is as in the above list.


Bountiful Airport Brigham City Municipal Airport

Spanish Fork Airport

Heber City Airport

Logan-Cache Airport

Figure 16 Airport Layouts

As Figure 16 illustrates, a good combination of runway sizes is considered in the test locations. The size of the airports affects the aircraft mix operating in the airport as well. That said, a good mix of aircraft types has been captured in the conducted data collections. For example, Bountiful Airport has high light aircraft traffic. The challenges associated with light aircraft detection and recognition are their small sizes and irregular tail number shapes compared to bigger aircraft, such as airliners.

On the other hand, Spanish Fork Airport and Brigham City Municipal Airport host a more mixed aviation fleet. A wide range of aircraft types, from light aircraft to heavier planes, are seen during data collection. This fact creates another challenge for aircraft operation recognition since the wider range of aircraft results in a wider range of aircraft operation speed, acceleration, and landing approach. This set of data helps us further customize the software for such airports.

Heber Valley Airport had the most jet traffic among the test locations. This type of aircraft tends to operate (depart or land) at a much higher speed and acceleration compared to the other aircraft. The higher operation speed increases the blurry effect in the recorded video frames. Consequently, a higher rate of video data recording might be critical for accurate aircraft operation detection at these airports.

Logan-Cache Airport was originally selected to assess the system performance for more complex taxiway-runway arrangement cases. As the plots illustrate, the operations at this airport involve three runway lanes with the associated taxiway and taxiway-runway passages. In the conclusion section, the strategic passages that control the majority of the activities in these airports are recognized and evaluated for optimum placement of the cameras. In the next section, the finalized video data quality for aircraft operation detection and classification is presented.

3.2 Specifications

The dataset was collected with low-priced commercial off-the-shelf cameras (GoPro Hero 8, GoPro Hero 3, and Fuji Film XT-30) mounted on steel tripods. Several recording resolutions are tested, including 4K linear, 4K wide, 2.7K (1.4x), 1080 (HD) (2x), XP+, and 1760x3120 (2x). Based on the results, 1080 video resolution with 30 frames per second and 2x zoom selected is best since it ensures enough pixel and number of frames in a flight operation time window for aircraft detection and operation count. However, the increase in video resolution can help with the task of aircraft identification through recognition of its tail number. The system evaluation section illustrates the extent to which increased video resolution affects the results of the aircraft identification in both camera layouts separately.

We conducted several data collections at the assigned test locations to have a wide variety of video data, including all possible variations. These variations are, but are not limited to, different weather/illumination conditions, other moving objects in the scene, different airport layouts, and different aircraft types. The project lead visited all five test locations during the project time and conducted multiple data collection sessions at each airport. With the assistance of the student team, the project lead has conducted 29 data collection sessions in total in all 4 seasons of the year (i.e., 2020-2021). The following pictures display a few screenshots of the camera FoVs as well as the equipment setup at some of the data collections.

Skypark 09-25-2020

Skypark 09-28-2020


Skypark 10-14-2020


Brigham City Municipal Airport 10-28-2020


Brigham City Municipal Airport 11-18-2020


Brigham City Municipal Airport 11-19-2020

Skypark 12-10-2020

Skypark 12-15-2020

Skypark 12-16-2020

Spanish Fork Airport 12-23-2020

 

Spanish Fork Airport 02-19-2021

 

 

Heber Valley Airport 06-03-2021

 

Heber Valley Airport 06-04-2021

Logan-Cache Airport 08-10-2021

Figure 17 Sample screenshots from cameras FoVs

Figure 17 correctly shows the variety of aircraft types and the different shapes of the associated tail numbers printed on the aircraft fuselage. In some cases, the aircraft's small tail number size is even hard for human eyes to read. The direct sunlight towards the aircraft body is another example of a not-readable aircraft tail number. While a polarizer filter can alleviate the sun radiation into the camera lens, the radiated sunlight to the aircraft body still escalates the tail number reading possibility. In cases where the sun shines directly into the camera lens, an IR cut lens can moderate the effect of the input light into the camera lens.

Figure 18 Data Collection Setup

As the pictures in Figure 18 illustrate, all data collections are distributed throughout different seasons of the year for a better generalization of the research product. From the beginning of the project, the project leader collected the required data with a crew from Dr. Rashidi and Dr. Markovic's lab. After each data collection, the video footage is meticulously assessed and processed with the developed algorithms (software). Several trials and errors have been made before having the most current software platform and camera layout configuration. Of them, we can point to video configurations and camera specifications, camera positions at the airports, and software debugging. The next section evaluates the system using the collected data from the assigned test locations (airports).

3.3 Summary

Five public-use airports are selected for the data collection test locations. These airports are within the state of Utah and selected to have a wide variety of data, including different aircraft operations (propeller, jet, etc.), various airport layout plans, and different airport sizes. Also, the data collections are distributed throughout different seasons to have a wide range of weather and illumination conditions, including sunny, overcast, snowy, and rainy.

4.0 SYSTEM EVALUATION

4.1 Overview

We evaluate the designed system by standard metrics. First, the aircraft operation capture by camera layouts is assessed. Next, we report the accuracy of the computer vision algorithms, including aircraft operation detection and tail number identification.

4.2 System Accuracy

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 288 and 91 for camera layout 1 and camera layout 2, respectively (Table 2).

As indicated in Table 3, camera layout 1 field of view had 99.3% accuracy regarding FoV selection in the airport environment for capturing flight operations (i.e., departure operations and landing operations, including arrivals and touch-and-goes). Moreover, the software detected 96.9% of the captured flight operations in the video footage in layout 1. Similarly, the layout 2 system had 100% accuracy for camera FoV selection and 95.8% accuracy for operation detection via our vision-based software. Figure 19 and Figure 20 display the AIVATS software output displayed on the video footage screen (layouts 1 and 2) for further illustration.

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	79	79	76	52	52	52
Landing*	209	207	201+ 1**	39	39	38
Total	288	286	277	91	91	90

*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 distinguishing tasks. From 377 operations captured by cameras, only ten false-negative detections and one misclassification (i.e., false-positive) have resulted from 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	99.3%	100%
Software (automatic vision based)	96.9%	95.8%
Camera + Software	96.2%	95.8%

Figure 19 AIVATS software performance during (top image) and right after (bottom image) the aircraft operation in layout 1

Figure 20 AIVATS software performance during (left image) and right after (right image) the aircraft operation in layout 2

Despite having a slight accuracy difference for operation count and operation status recognition 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 5% 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 reasons for the increased identification accuracy in layout 2. The remaining errors are due to the visibility of the tail numbers (e.g., their sizes), and sometimes they are cluttered/unclear. Furthermore, in about 6% of the cases, the operating aircraft did not have an imprinted tail number at all (Figure 21).

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

		Layout 1	Layout 2
% (correctly) identified		64%	80%
% unidentified	Aircraft with no printed tail number	7%	6%
	Not visible (small, cluttered, unclear tail numbers)	15%	9%
	Software error	14%	5%

Figure 21 Aircraft with small, cluttered, and not imprinted tail numbers

4.3 System Processing

In order to decrease the data congestion as much as possible, several algorithms are improved. In addition, the project lead switched the programming software backend from MATLAB to Python, which is about 10 times faster. Table 4 shows the processing times for the defined modules.

Table 5 Algorithms' processing times

Programming Platform	**Processing Time (seconds)**					
	SYS 1 and SYS 2				Only SYS 2	
	Motion Detection	Operation Tracking	Trajectory Post-Processing	Aircraft Detection (YOLO)	RD	OCR
MATLAB	0.2	NA	0.1	NA	A	NA
Python	0.02	0.02	0.01	0.3	.2	0.05

As Table 5 tabulated, the overall processing time of layout 1 is 0.35 seconds per frame, and this number is 0.6 seconds for layout 2. The most computationally expensive algorithm is aircraft detection using YOLO. That said, the project lead considered the following solutions to increase the software speed even more.

- Using smaller sized video frames
- Reducing the number of captured frames per second
- Using more powerful computers
- A new Aircraft Detection algorithm (YOLOV4 /SSD / Haar-Cascade Classifier)

As for the last solution, we implemented three other state-of-the-art algorithms to improve the speed. For YOLOv4, a similar deep neural network to YOLO architecture is used with some internal layer differences such as the size of the convolution filters and activation layers. SSD, which stands for single-shot detector, is another fast deep learning-based object detection method in imagery data. Figure 22 displays the picturized architecture of this deep neural network which is constructed with less fully connected layers compared to YOLO, which is one of the main reasons for being faster. The last method that is implemented for the aircraft detection module is a very fast object detector that works based on Haar features and is named Haar Cascade classifier.

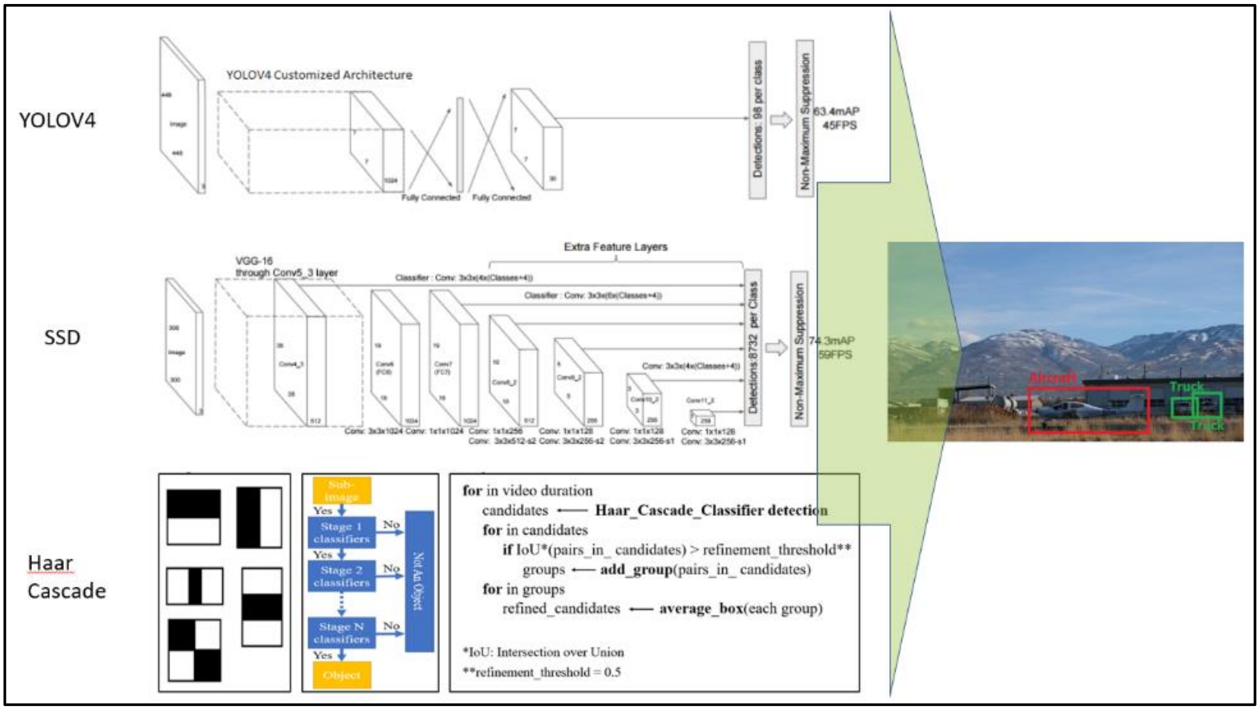

Figure 22 Schematic architecture of the YOLOv4, SSD, and Haar cascade object detectors

Table 6 shows the improved processing times using the described and implemented algorithms and their resulting accuracy in two columns. They are tested for both layouts and have different accuracies for each system because of the difference in the range of the view in the two camera layouts. By using YOLOv4, the processing time of detecting aircraft is reduced from 0.3 seconds to 0.1 seconds. As can be seen in the second column, SSD and Haar cascade were even faster. However, we need to choose the one that increases the speed while preserving good accuracy, so as numbers tell, considering both accuracy and speed, YOLOV4 is the one that is a good option for the backend of the software for system 1. This algorithm promises accuracy of more than 95% for the task of aircraft detection and, at the same time, decreases the processing time from 0.3 seconds to 0.1 seconds.

Table 6 Aircraft detector algorithms' performance

Algorithm	Processing Time(s)	SYSTEM 1 Accuracy	SYSTEM 2 Accuracy
YOLO	~0.3	>97%	>99%

YOLOV4	~0.1	>95%	>99%
SSD	~0.05	>55%	>93%
Haar Cascade	~0.02	>65%	>63%

On the other hand, SSD is the best choice for system 2 because of its faster detection while at the same time offering accurate detection. With improving the aircraft detection algorithms in our software, the processing time of both systems is decreased (improved) by about 2 to 3 times. This will help with less data congestion. Table 7 shows the finalized speeds in each camera layout for counting and identifying tasks separately. It should be noted that the inference times are benchmarked on a CPU-only-inference system. Thus, an NVIDIA GPU can increase the software speed as well.

Table 7 Improved software speeds (processing time)

Camera Layout Number	**Total Processing Time (seconds)**	
	Counting task	With TNR* task (identification)
SYSTEM 1	0.15 (7 fps)	0.4 (2.5 fps)
SYSTEM 2	0.1 (10 fps)	0.35 (3fps)

Note: TNR = Tail Number Recognition

5.0 CONCLUSIONS

5.1 Summary

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

The product of the design can be beneficial for aviation authorities to keep records of the activities of local airports under their jurisdiction. In addition, the system will be easy to implement and use at any non-towered airport with almost any airport layout plan. There are more than 20,000 non-towered airports across the U.S., and the AIVATS system is applicable for these specific airports.

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 detailed air traffic data in their airports. This data will be essential for future airport improvement plans, including operational, financial, and environmental. The results of the project are also disseminated through the community of interest in journal and conference papers (Farhadmanesh et al., 2021c, Farhadmanesh et al., 2022a, Farhadmanesh et al., 2022b, and Farhadmanesh et al., 2022c).

5.2 Limitations and Challenges

This system requires camera installation for the time period of airport operation monitoring. However, the airport airfield usually does not have the electrical infrastructure to support the power for the camera platforms. This challenge can be tackled by using solar panel-based chargers and chargeable batteries. Each camera battery can be directly charged with one solar panel power station.

The aircraft detection system could be used to provide operators and users with runway clearance, preventing runway incursions. To that end, an electrical engineer can use the results of aircraft detection for signalizing runway clearance information to pilots. However, it might confuse pilots while operating rather than enhancing their situational awareness due to the possible misdetections. In addition, it is absolutely critical to note that such a feature is restricted by FAA regulations as any distracting factor could lead to an unsafe situation. As a result, this feature is not recommended until the electrical engineer developer can guarantee its use.

5.2.1 OCR-Friendly Aircraft Tail Numbers

The developed system uses visual information of the in-field cameras. As a result, aircraft identification depends on the readability of tail numbers. That said, some factors might cause misidentification or not identifying an aircraft operation. As discussed in the data collection section, these factors include small tail numbers, abnormal/cluttered tail number shapes, aircraft with no imprinted tail number on the body, and extreme illumination conditions (e.g., direct sun radiation to the side of the operating aircraft).

The developed image pre-processing modules can improve the quality of the tail number images to look more readable than the original image. However, there is an important factor to mention. The image information should be retrievable before using these techniques. And if the tail number background or alphabet are cluttered, these algorithms might not be as helpful as they are in recovering the retrievable tail numbers.

As discussed with the TAC members, a few examples of OCR-friendly tail number appearances are provided in Figure 23. In this figure, simply good and bad instances are shown in two columns. On the left (good instances), the imprinted tail numbers appear large enough with distinguishable characters which are distanced with sufficient space in-between so human eyes can easily detect every character. As instances show, a slight inclination does not hurt the OCR results. Nevertheless, it is recommended to have manufacturers print the tail numbers with as little inclination as possible. That said, the first two examples in the good instances (i.e., N130BF and N287SC) are considered among the most desirable tail number appearances for the task of automatic/computerized vision-based tail number character recognition.

Good Instances (OCR-friendly) | Bad Instances (not OCR-friendly)

Figure 23 Aircraft tail number appearances with OCR-friendly classification

It is recommended to avoid printing small tail numbers and print them as big as possible, considering the size of the aircraft fuselage (e.g., N492DS and N22QQ). The tail number is better to be at least 12 inches high. Characters must be two-thirds as wide as they are high, except the number “1”, which must be one-sixth as wide as it is high, and the letters “M” and “W” which may be as wide as they are high. Characters must be formed by solid lines one-sixth as thick as the character is high.

No line or any other design should be incorporated in the background of the tail numbers. The best background would be a plain color (e.g., white if the numbers are printed in a dark color). “N732HD” (fourth row, second column) is one not OCR-friendly example with a cluttered background. The tail number must contrast in color with the background, be legible, and have no ornamentation (Code of Federal Regulations, Title 14, Part 45-Identification and Registration Marking, Subpart C-Nationality and Registration Marks).

It is strongly recommended to print the tail number considerably larger than other texts on the aircraft fuselage to avoid any misidentification caused by printed irrelevant numbers. See the picture on row seven in the second column (small tail number: N5074H, the irrelevant number printed in large font-size: 01417). Also, the marks required by this part for aircraft are recommended to have the same height, width, thickness, and spacing on both sides of the aircraft.

Closely arranged tail numbers with insufficient space between the characters of the tail numbers are another example of not OCR-friendly tail numbers. The space between each character may not be less than one-fourth of the character width (Code of Federal Regulations, Title 14, Part 45-Identification and Registration Marking, Subpart C-Nationality and Registration Marks). The picture on the fifth row, the second column (N787HD), clearly shows an example of a difficult-to-read tail number even at a close range of view. This tail number also suffers from a difficult-to-read font shape which could be corrected with an easily readable font shape similar to the first two pictures in the first column (i.e., N130BF and N287SC). The following pictures illustrate the result of applying a strong tail number region detection algorithm (in a yellow box) and OCR machine (in a pink font) on aircraft pictures. It should be noted that the distances that cameras are placed in camera layout 1 pose more challenge to read the tail numbers.





Figure 24 TRD (yellow box) and OCR (pink font) results on sample photos from aircraft parked in the apron area

<u>5.2.2 Nighttime Operation</u>

Infrared night vision cameras are a practical solution for capturing aircraft operations during the night with less visibility. Nonetheless, most of the off-the-shelf cameras with infrared night vision are effective for close ranges less than 50-70 feet. As a result, use of night vision cameras greatly benefits the camera layout 2 in cases where we can install cameras adjacent to the taxiway-runway connector and as close as the determined camera night vision range.

Runway lighting also might alleviate nighttime visibility problems. At some airports, this lighting is actually strong enough to perform the task of aircraft operation count. However, the identification task requires much more visibility to ensure tail number reading through the OCR machine. Figure 25 is a screenshot from video footage captured from the Spanish Fork Airport runway area using a camera in camera layout 1. As shown, the aircraft is quite visible thanks to the runway lighting at this specific airport. During the three nights of data collection at the Spanish Fork Airport, only one operation took place. This highlights the lower frequency in nighttime operations relative to daytime operations as there were more than 100 operations during the same time during the day.

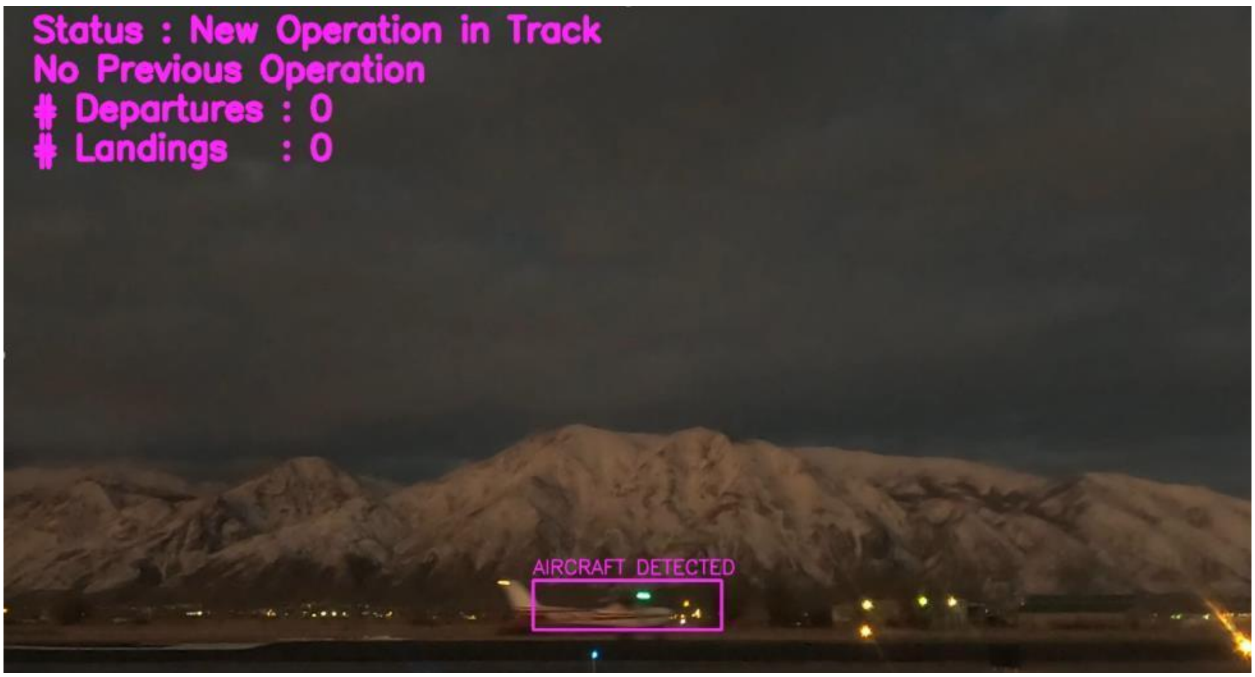

Figure 25 A screenshot of a nighttime operation captured with a handheld camera (which explains the blurriness); the aircraft is detected, and the operation is correctly counted with the correct operation status (i.e., departure)

ACRP Report 129 (Muia and Johnson, 2015) also includes real data of aircraft activities at Tri-City State Airport with an hourly classification of the operation occurrences. The provided data is for 14 consecutive days (two weeks) with zero aircraft activity between the hours of 8:00 PM and 6:00 AM. As a result, if system performance is reduced at night at airports with no lighting, that might be slightly mitigated by much fewer nighttime flights. Moreover, it is expected to have a lighting facility at those airports that expect a higher nighttime operations rate.

5.3 Recommendations

In this report, two camera layouts are proposed to relax the video-based system for a wider range of airports with different layouts and sizes. Camera layout 1 is a perfect choice in cases where accuracy of aircraft operation count/classification is of great importance while maintaining a low system cost. This layout will allow an accurate airport operation count in any type of airport layout and size. In this layout, each runway lane (in the case of multiple runways) is covered with a two-camera system. The lower number of cameras will reduce the requirement for the processing platform (computers) as well. Unlike the existing operation counting systems, layout 1 can detect and classify all landings (touch-and-goes and arrivals) and departures.

In cases where higher aircraft identification accuracy is desired, camera layout 2 is an appropriate alternative. Although this layout requires a higher number of cameras (one at each connector), the closer range of view allows us to use cheaper cameras and lower video resolutions for accurate aircraft detection/identification. In addition, this layout facilitates the calculation of the touch-and-go activities rate in the airport. All in all, several factors should be considered before choosing the camera layout type. These factors include but are not limited to expected operation counting accuracy, expected aircraft identification accuracy, rate of the airport's training-related activities, allocated budget, airport taxiway-runway connectors' configuration, placement of the hanger area, the distance between taxi lanes and runway lane, and the airport location. These factors will be considered when choosing the right camera layout for the five test locations in the implementation section (next section).

5.4 Implementation

In this section, we will first review the instructions for how to record the footage from the airports' airfield considering the requirements of each camera layout separately. A sustainable solution for camera installation is proposed. Subsequently, this section describes how to process the recorded videos to count airport activities and identify the aircraft.

5.4.1 Camera Installation

Basically, we first record the videos based on the following recording setup specifications. A solar-powered camera is suggested for a sustainable recording system so that no battery change would be required. Some of the cameras come with spotlights which are helpful for night vision. However, as stated before, the night vision cameras' range is usually limited to 50-70 feet. Figure 26 shows two examples of the above-mentioned cameras.

The cameras should be able to record videos with at least 1080x1920 video resolution (also known as the HD resolution). Higher resolutions will increase the accuracy of the identification through recognition of the aircraft tail number. The HD resolution is more than enough for cameras in camera layout 2. It is critical to make sure of the original HD resolution of the cameras since there are some cameras on the market with "fake" HD resolution. One way to make sure of the quality of the camera is to use their digital zoom, and the user must be able to recognize an aircraft tail number from distances of about 170-180 feet (camera layout 1 distance from the runway centerline). The zoom should be set to about 2x (using the digital zoom or the mounted zoom lens of the camera). In cases of wider TSA and RSA at larger airports where more distance from operating aircraft is imposed to place the camera, the amount of zoom should be increased accordingly to achieve the same field of view in the footage of a 2x zoomed camera placed 170-180 feet away from the runway centerline.

Figure 26 Solar powered cameras; night vision cameras

Cameras at camera layout 1 can be placed farther than 180 feet if a higher than 2x digital zoom is provided by the digital camera. If the cameras are placed behind the taxiway lane, a minimum elevation should be provided to avoid capturing the taxiing aircraft. No digital zoom is required for cameras that are going to be used in the camera layout 2.

Since in camera layout 1 the cameras target the runway area and fast-moving aircraft (either landing or departing), at least 24 frames per second are required, especially in landing operation cases. The collected data from several data collection sessions shows that the landing operations time windows vary between less than one second to about 2-3 seconds, depending on the camera field of view and the aircraft size and speed. Accordingly, 24 frames per second can guarantee the cameras do not miss the landing operations, provided that the cameras are placed at the designated distances. In camera layout 2, however, a minimum of 10 frames per second would suffice.

Cameras with 4G SIM card connectivity let us view/check the field of view of the camera during the process of camera installation. In addition, if it has a stable data service, the 4G SIM card can be used to restore the video on a cloud. However, if the data service is not stable enough, an SD card should be used to transfer the recorded videos to the computer center.

5.4.2 Optimum Placement of Cameras

As discussed, two camera layouts are devised to have a conducive system for airports with different configurations. The following briefly enumerates each camera layout feature:

- Camera Layout 1:
  - Two cameras for each runway lane
  - Counts Departures and Landings
  - Less accurate identification compared to camera layout 2
- Camera Layout 2:
  - One camera at each strategic passage (necessary intersections and connectors)
  - Counts Departures, Arrivals, and Touch and Goes
  - More accurate identification compared to camera layout 1

However, different airport layouts are another important factor that should be taken into account when choosing the right camera layout. Thus, we evaluate each of the five test locations (airports), considering the influential factors for choosing the right camera layout.

1. Bountiful Airport (Skypark)

i. The large number of connectors (Figure 27)
ii. De-centralized terminal area
iii. Narrow runway and taxiway arrangement
iv. Moderately short runway

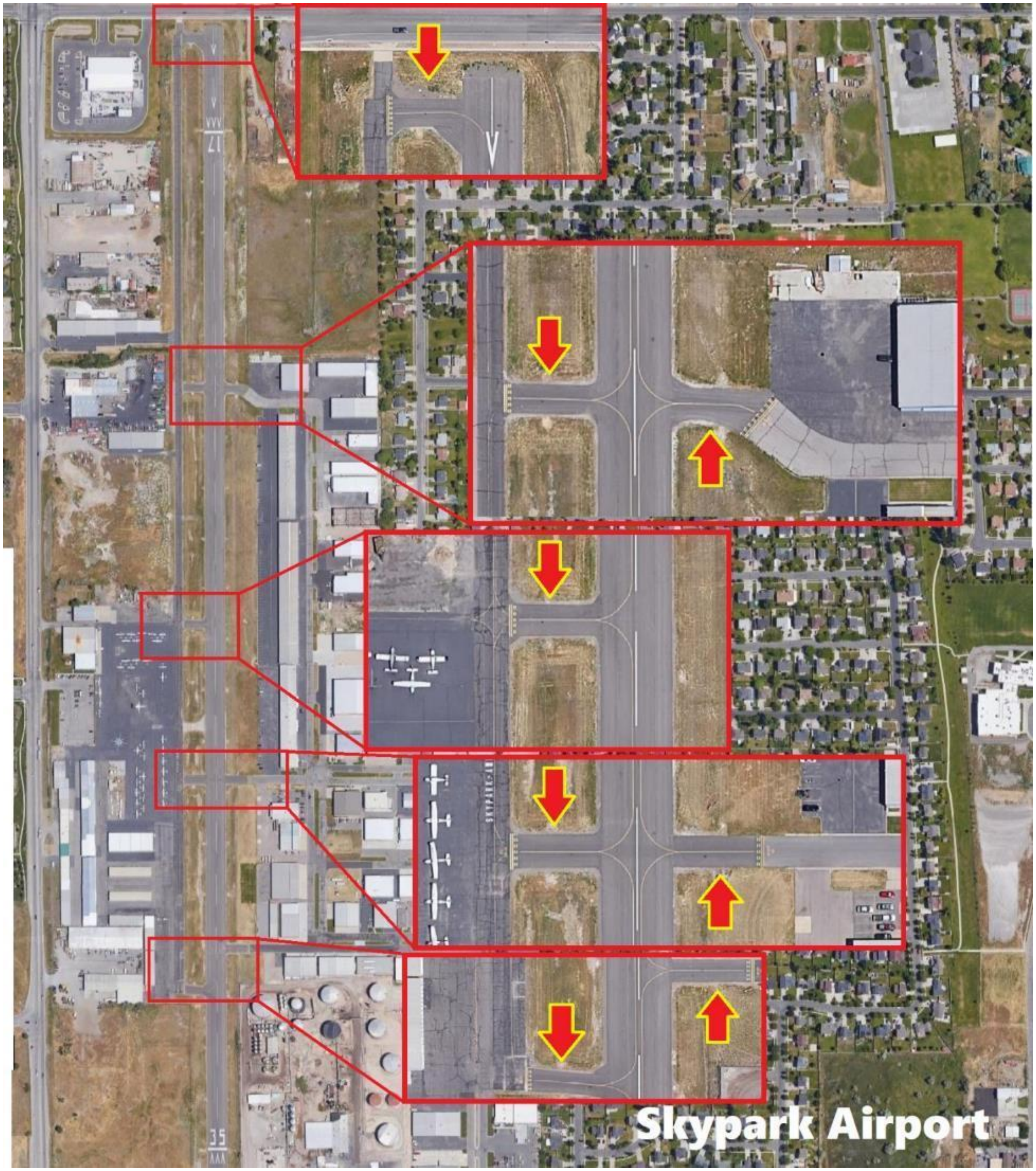

Figure 27 Bountiful Airport (Skypark)

All these factors considered, camera layout 1 with having one camera at each end of the airport is the best solution for this airport. The closer arrangement of the runway and taxiway moderates the long range of view of camera layout 1 and makes it slightly easier for aircraft identification as well.

2. Brigham City Municipal Airport

   i. The small number of connectors (Figure 28)
   ii. Centralized terminal area
   iii. Wide runway and taxiway arrangement
   iv. Moderately long runway

Figure 28 Brigham City Municipal Airport

Quite contrary to the Bountiful Airport, Brigham City Municipal Airport has fewer corridors with a centralized hangar area and limited access area. This makes camera layout 2 a good solution for this airport. The cameras also could be deployed only on the two strategic locations designated in Figure 28 to keep the record of the aircraft operations.

3. Spanish Fork Airport

    i. Centralized terminal area (Figure 29)
    ii. Wide runway and taxiway arrangement
    iii. Moderately long runway

Figure 29 Spanish Fork Airport

At Spanish Fork Airport, with only about three cameras at the designated locations (passages), a new version of the camera layout 2 can count and identify the operations at this airport. This selection of the camera layout is due to the centralized terminal area and the long runway at this airport.

4. Heber Valley Airport

   i. De-centralized terminal area (Figure 30)
   ii. Narrow runway and taxiway arrangement

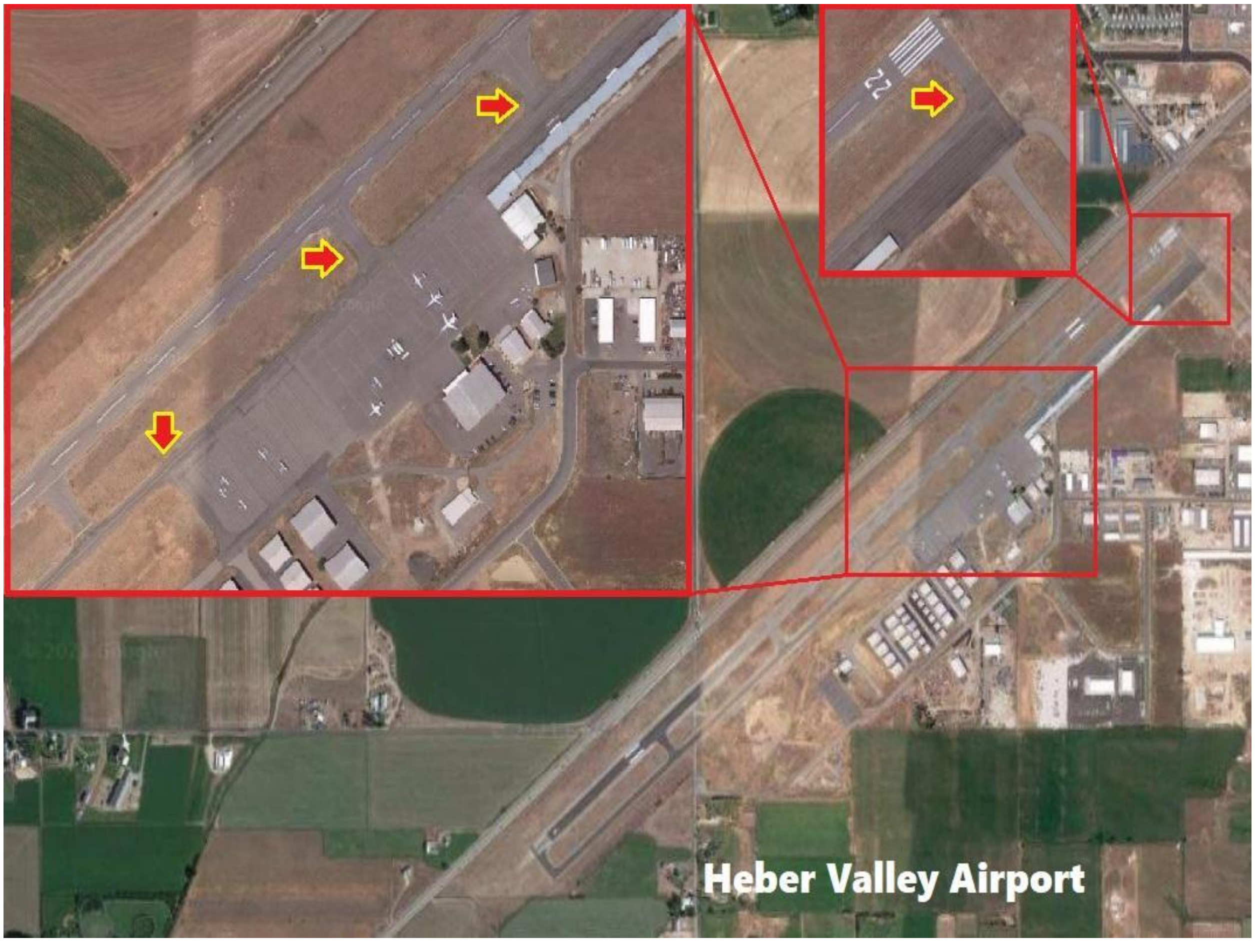

Figure 30 Heber Valley Airport

Heber Valley Airport has two main apron areas (Figure 30), which makes the terminal area decentralized. So, camera layout 1 would be a better option regarding the counting task and the number of cameras. Still, camera layout 2 with four cameras at the designated locations can guarantee higher aircraft identification accuracy.

5. Logan-Cache Airport

    i. Three runway lanes (Figure 31)
    ii. Centralized terminal area
    iii. Wide runway and taxiway arrangement
    iv. Moderately long runway

Figure 31 Logan-Cache Airport

At Logan-Cache Airport, considering the number of runway lanes and arrangement of the runway and taxiway lanes, camera layout 2 is both cheaper and more accurate. It is cheaper since in the case of camera layout 1, we would need two cameras for each runway lane which adds up to 6 cameras. In comparison, only 3 cameras at the designated locations are required to capture the aircraft activities at Logan-Cache Airport. The three determined passages can capture all activities interchangeably. Additionally, in the case of camera layout 1, cameras might overcount the other runway lanes' operations. As a result, camera layout 2 is also more accurate due to the centralized terminal area.

5.4.3 Processing Platform

For processing the recorded video footage, a processing computer equipped with an NVIDIA GPU is needed. It is noteworthy that with GPU-accelerated inference, the user can increase the processing speed and process the video data in a shorter amount of time. The processing times reported in the system evaluation section are benchmarked on a system with CPU-only inference. The main library that is used to develop the algorithms is OpenCV which needs to be installed on the processing computer.

OpenCV is a library of programming functions mainly aimed at real-time computer vision. Originally developed by Intel, it was later supported by Willow Garage then Itseez. The library is cross-platform and free for use under the open-source Apache 2 License. In this project, Python is the backend programming language used for implementing the OpenCV library and other dependencies (Xlrd, NumPy, Pandas). More precisely, version 4.4 OpenCV with installed Python 3 is used for aircraft detection and tracking modules. It should be noted that the user must build the OpenCV package from the source to be able to benefit from the feature of GPU-accelerated inference in their processing platform.

5.4.4 System Cost

The system's total cost can be divided into research and development and operation costs. Expenses related to designing the computer-vision framework and conducting field test experiments covered the research and development costs. The equipment cost and maintenance cost comprises the operation costs of the developed vision (camera) -based system. Table 8 lists the approximate prices of the required equipment.

Table 8 Equipment Costs

Item	Rate	Quantity	Subtotal		Remarks
Processing Platform					
Processing computer equipped with NVIDIA GPUs	$2,000-$4,000	1*	$4,000		GPUs with a high number (>5,000) of CUDA cores are preferred
Software	-	-	-		The developed computer vision algorithms run on open access libraries
In-field video data recording					
			Layout 1	**Layout 2**	
Solar-powered digital cameras	$500-$1,000	2 to 4**	~$1,500	~$3,000	Hardware
Memory card	$50	2 to 4**	$100	$200	Hardware
Physical infrastructure for cameras	$100-$300	2 to 4**	$400	$800	Boxes and tripod legs
Miscellaneous	$50	2 to 4**	$100	$200	Box covers
Subtotal			**Order of $2,000**	**Order of $4,000**	Data Recording Cost
			Order of $4,000		Processing Platform Cost

Note: *More processing platforms can accelerate the processing time in the office
**Depending on the number of required units for layout 2

Installation and maintenance costs are listed in Table 9. In other words, the cost of permanent system assembly (equipment and installation) totals approximately $8,000 for layout 1. The remaining cost would be the maintenance cost which differs based on the desired period for deploying the system (Table 9). Based on the ACRP report 129 for counting non-towered airport operations, a period of 2 weeks to 1 month is suggested per each season sample if a statistical method is employed to estimate the annual operation volume accurately.

Table 9 Non-equipment related operation cost

Item	Rate	Quantity	Subtotal	Remarks
Software and hardware installation				

Electrician	$70/hr	~10 hrs.	$700	Cameras
Computer Engineer	$80/hr	~10 hrs.	$800	Software
Worker	$30/hr	~10 hrs.	$300	Camera infrastructure
Maintenance				
Technical Support*	$30	~10 per month	$300	Transferring data from cameras to the computer center*
Subtotal			**Order of $2,000**	Permanent Installation
			Order of $4,000	Maintenance per year

Note:*Varies depending on the used memory device capacity and the recorded video file sizes (resolution) if the 4G SIM card data service is not stable enough

With the aforementioned cost, the intelligent vision (camera) -based system offers accurate aircraft operation count, activity recognition, and aircraft operation identification for the deployment period at the target airport. Aircraft counting equipment tested by ACRP (under Report 129) included automated acoustical counters, sound-level meters, security/trail cameras (manual counting), and ADS-B. Each of these has their advantages but also come with many disadvantages, including accuracy, installation problems, cost, speed, and feasibility (e.g., the market penetration rate). Additionally, none of them can effectively and automatically identify operating aircraft. More precisely, acoustical and sound-based counters are designed primarily for operation count. On the other hand, ADS-B-based systems depend on the aviation fleet equipage rate with ADS-B out (transponders). However, the current equipage rate is low (only about 57% [FAA, 2020]), and the transponders of most of the equipped civilian aviation fleet (about 84%) are incapable of transmitting Mode S signal that contains aircraft identity information. Consequently, this system cannot identify even a large portion of the equipped aviation fleet. Besides, the dependency of this system's performance on an auxiliary electronic unit to be mounted on aircraft decreases the reliability of using it, especially for assisting the process of billing the landing fees. A system that does not depend on the cooperation of the operating aircraft can properly address this issue.

5.5 Spin-Off Benefit

One spin-off benefit of the developed algorithms is that they can be adjusted to automate the aircraft tallying process through the Security/Trail Camera (ST/C) aircraft counting method. In this method, Security/Trail Cameras take photos when any motion is sensed, and later the photos are manually processed to see if the images contain an aircraft or not. The photos might contain wildlife, airport service vehicles, airport personnel, and/or aircraft (Figure 32). The algorithms can be adjusted to help with the automation of this process, so it will be laborless and, of course, faster.

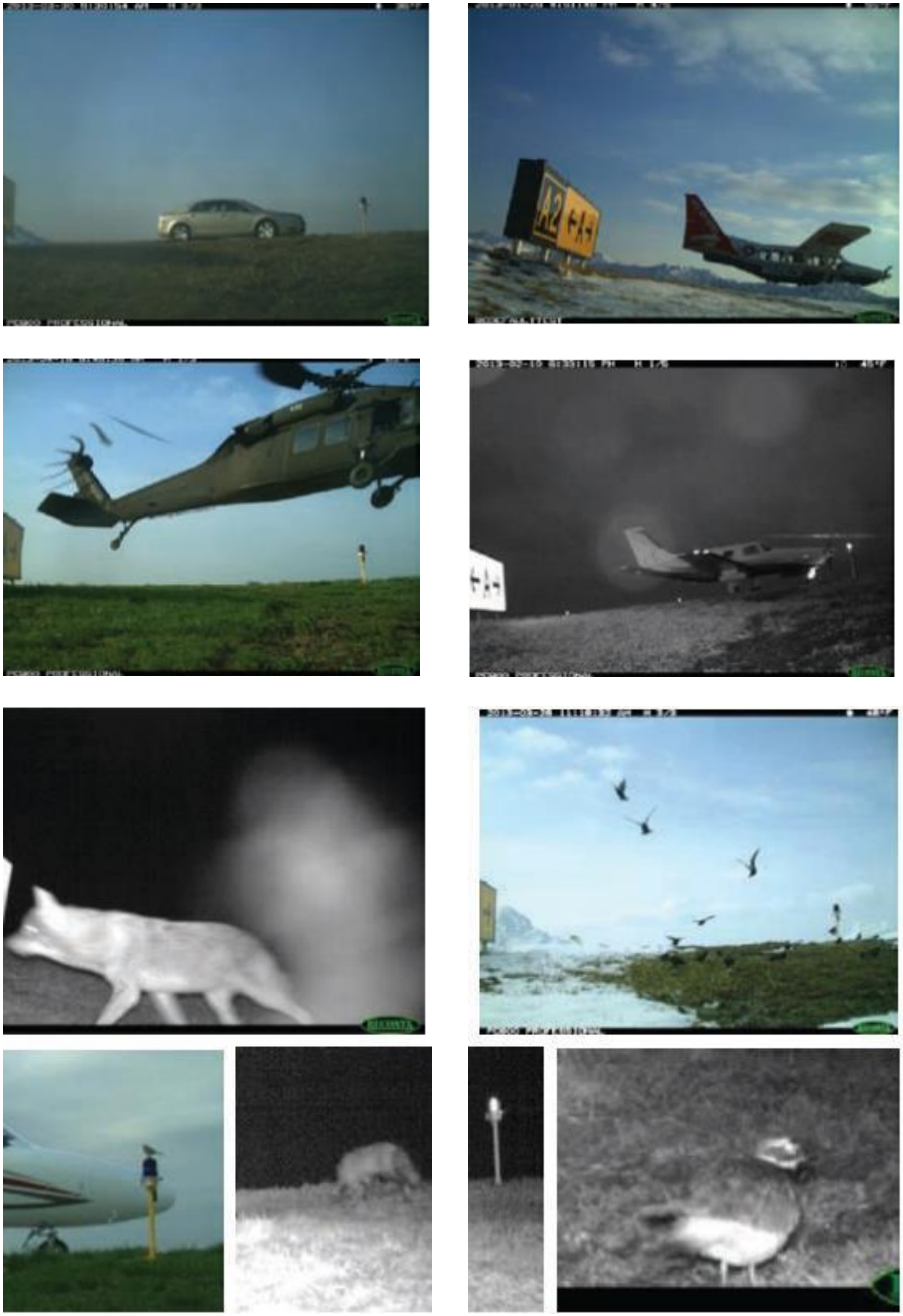

Figure 32 Photos taken by security/trail cameras

5.6 Future Extension Opportunities (Prototyping)

The project lead would like to highlight the fact that this project was on proof of concept of developing necessary algorithms and hardware. A potential extension to this project could be prototyping the developed systems and algorithms and converting the framework into a stand-alone device deployable at airports. The development of such a stand-alone device is a complex project and requires a single board computer as the main processor and electronic engineering along with the required software adjustment and, of course, an industry mentor to conduct the pilot experiments (Figure 33).

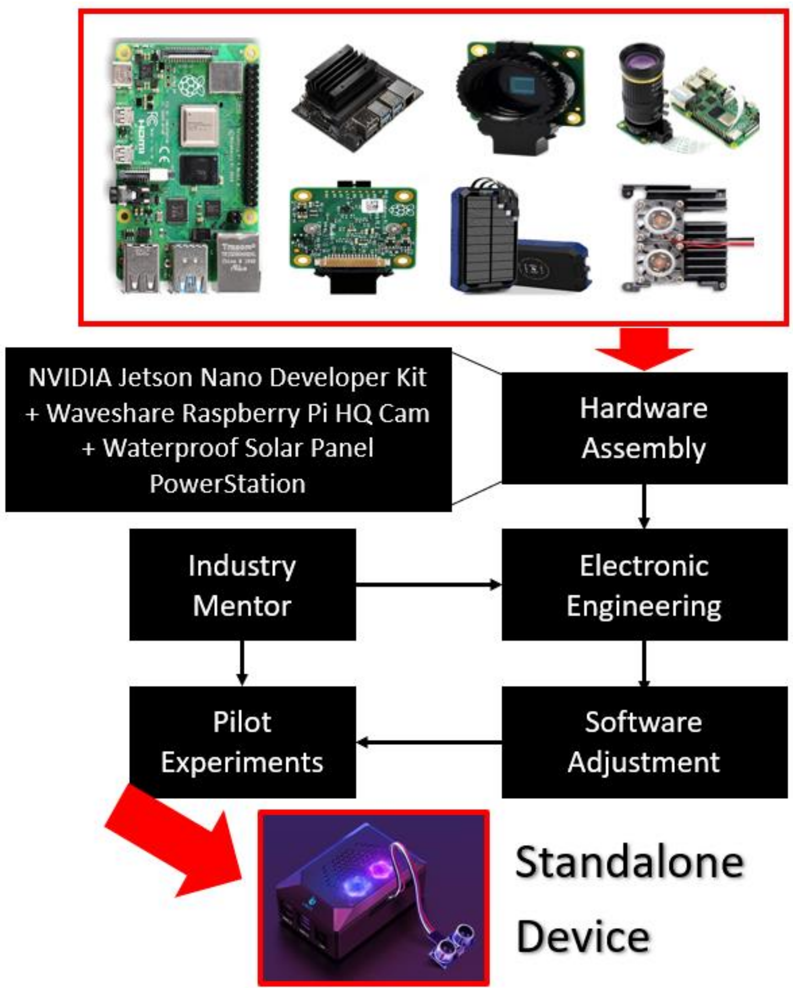

Figure 33 Stand-alone device prototyping process

5.6.1 Cost Analysis

In this section, we assess the practicality of implementing a stand-alone device for automatic air traffic counting at airports by analyzing the system cost. The edge system's total cost can be divided into design/field tests and operation costs. The framework design/field test expenses cover the project time needed to spend for research and development of the product prototype. Table 10 tabulated the detailed costs of research and development, including labor, travel, and equipment.

Table 10 Stand-alone device research and development cost

Item	Rate	Quantity	Subtotal		Remarks
Labor - University Design Competition					
Manpower	$25/hr	1400 hr	$35,000		Engineer
Travel	$0.54/mi	2000 mile	$1,080		Airport visits
Expenses (equipment for **one unit**)					
			Layout 1	**Layout 2**	
NVIDIA Jetson Xavier Developer Kit	$399	2 to 4*	$798	$1,596	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	$100	2 to 4*	$200	$400	Hardware
Waterproof Solar Panel Powered PowerStation	$300	2 to 4*	$600	$1,200	Hardware
Miscelleneous	$100	2 to 4*	$200	$400	Case
Subtotal			**Order of $2,000**	**Order of $4,000**	Complete package
			Order of $45,000		Total Cost

Note: *Depending on the number of required units for layout 2

As the table demonstrates, an engineer with computer science expertise is required to conduct the necessary electronic engineering tasks for assembling a stand-alone device. The different amounts of equipment needed in layout 1 and layout 2 design of the stand-alone device affect the total cost per unit. The estimation for preparing the complete package for layout 1 and layout 2 totaled $2,000 and $4,000, respectively, plus the labor cost regarding the electronic and software/hardware engineering, which approximately totals $45,000.

With the completed system development stages, the system operation requires an installation plan and regular maintenance conducted by technicians and computer engineers. A monthly troubleshooting plan is considered to conduct the service. Table 11 represents the associated costs of system operation over an operational period of three years. The proposed video-based system provides the airport industry with an aircraft operation count, which supports future federal and state planning and funding allocations.

Table 11 System operation costs

Item	Rate	Quantity	Subtotal	Remarks
Labor for installation				
Electrician	$70/hr	10 hrs.	$700	1 worker
Computer Engineer	$80/hr	10 hrs.	$800	1 worker
Labor for maintenance				
Technical Support	$100/day	36 inspection sessions	$3,600	Once per months
Subtotal			$5,100	Per unit for 3 years
			Order of $2,000	Maintenance per year

Comparing the cost of the system with an automated acoustical counter (AAC) can easily show the benefit of using the vision-based operation counting system. AAC counters are among the most common systems used by airport authorities to measure the volume of their domestic operations. Based on ACRP Report 129 released in 2015, an AAC counter costs approximately $5,000 per unit, and it should be noted that for most cases, multiple counters are needed (e.g., in 92% of the cases, three counters are needed on a single 5,500 foot runway). As a result, the AAC system costs more than the vision-based system since the 1st layout of the vision-based system can monitor a 6,000 ft long runway with two units with an overall equipment cost of $2,000 and a maintenance cost of $2,000 per year. Notably, a vision-based counter has shown higher accuracy (more than 90% based on the conducted tests for assessing the system performance). According to Mott and Sambado (2019), the accuracy of acoustic devices is about 59% in counting the number of airport operations. This, in addition, shows the advantage of a vision-based system for measuring airport operations at general aviation and non-towered airports.

REFERENCES

AOPA. “Operations at Nontowered Airports” (PDF).

Billings, C. E. (1997). Aviation Automation the Search for a Human Centered Approach Lawrence Erlbaum Associates. *Inc., Mahwah, NJ*.

Cross, C., Farhadmanesh, M., & Rashidi, A. (2020). *Assessing Close-Range Photogrammetry as an Alternative for LiDAR Technology at UDOT Divisions* (No. UT-20.18). Utah. Dept. of Transportation. Division of Research.

Farhadmanesh, M., Cross, C., Mashhadi, A. H., Rashidi, A., & Wempen, J. (2021). *Use of Mobile Photogrammetry Method for Highway Asset Management* (No. TRBAM-21-01864).

Farhadmanesh, M., Cross, C., Mashhadi, A. H., Rashidi, A., & Wempen, J. (2021). Highway Asset and Pavement Condition Management using Mobile Photogrammetry. *Transportation Research Record*, 03611981211001855.

Invisible Intelligence <http://www.invisibleintelligencellc.com/gard-device-technology.html>. [Accessed Mar 24, 2021]

Airservices Australia. “How ADS–B works.” 28 November 2012.<https://www.airservicesaustralia.com/about-us/projects/ads-b/how-ads-bworks/#:~:text=ADS%2DB%20is%20a%20system,without%20the%20need%20for%20radar.> [Accessed March 11, 2021]

Koh, C. H. (2019). *Development of an algorithm for correlation of aircraft positioning data from radar and ADS-B sensors/Koh Che Hun* (Doctoral dissertation, University of Malaya). file:///C:/Users/civil/Downloads/Thesis-Final_20190101.pdf

Muia, M. J., & Johnson, M. E. (2015). *Evaluating methods for counting aircraft operations at non-towered airports* (No. Project 03-27).

Frequentis For a Safer World. Air Traffic Management. Whitepaper: Introduction to remote virtual tower. 2016. <https://www.frequentis.com/sites/default/files/support/2018-02/RVT_whitepaper.pdf>

Johnson, M. E., & Gu, Y. (2017). Estimating airport operations at general aviation airports using the FAA NPIAS airport categories. *International Journal of Aviation, Aeronautics, and Aerospace*, *4*(1), 3. <https://commons.erau.edu/cgi/viewcontent.cgi?article=1151&context=ijaaa >

Federal Aviation Administration. (2016). FAA Form 5010, Airport master record. Washington, DC: Federal Aviation Administration. Retrieved from http://www.faa.gov/airports/airport_safety/airportdata_5010/

FAA seal, "Automatic Dependent Surveillance-Broadcast (ADS-B)," 12-Mar-2019. [Online]. Available: https://www.faa.gov/nextgen/programs/adsb/. [Accessed: Mar 23, 2021]

Parlin Field. News and Events at the Parlin Field Airport in Newport, New Hampshire. <https://www.newportnh.gov/sites/g/files/vyhlif4776/f/uploads/newsletter_may_2014.pdf> [Accessed: April 1, 2021]

Federal Aviation Administration. (2021). https://www.faa.gov/nextgen/equipadsb/installation/current_equipage_levels/ [Accessed Feb 10, 2021]

Besada, J. A., Portillo, J., García, J., Molina, J. M., Varona, Á., & González, G. (2001, August). Image-based automatic surveillance for airport surface. In *4th International Conference on Information Fusion, Fusion* (pp. 11-18).

Alganci, U., Soydas, M., & Sertel, E. (2020). Comparative research on deep learning approaches for airplane detection from very high-resolution satellite images. *Remote Sensing*, *12*(3), 458.

Chen, H., Zhao, J., Gao, T., & Chen, W. (2018, July). Fast airplane detection with hierarchical structure in large scene remote sensing images at high spatial resolution. In *IGARSS 2018-2018 IEEE International Geoscience and Remote Sensing Symposium* (pp. 4846-4849). IEEE.

Xu, Y., Zhu, M., Xin, P., Li, S., Qi, M., & Ma, S. (2018). Rapid airplane detection in remote sensing images based on multilayer feature fusion in fully convolutional neural networks. *Sensors*, *18*(7), 2335.

Dey, D., Geyer, C., Singh, S., & Digioia, M. (2011). A cascaded method to detect aircraft in video imagery. *The International Journal of Robotics Research*, *30*(12), 1527-1540.

Fu, C., Carrio, A., Olivares-Mendez, M. A., Suarez-Fernandez, R., & Campoy, P. (2014, May). Robust real-time vision-based aircraft tracking from unmanned aerial vehicles. In *2014 ieee international conference on robotics and automation (ICRA)* (pp. 5441-5446). IEEE.

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

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 779-788).

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016, October). Ssd: Single shot multibox detector. In *European conference on computer vision* (pp. 21-37). Springer, Cham.

Rastegar, S., Babaeian, A., Bandarabadi, M., & Toopchi, Y. (2009, March). Airplane detection and tracking using wavelet features and SVM classifier. In *2009 41st Southeastern Symposium on System Theory* (pp. 64-67). IEEE.

Bolme, D. S., Beveridge, J. R., Draper, B. A., & Lui, Y. M. (2010, June). Visual object tracking using adaptive correlation filters. In *2010 IEEE computer society conference on computer vision and pattern recognition* (pp. 2544-2550). IEEE.

Molina, J. M., García, J., Berlanga, A., Besada, J., & Portillo, J. (2002, July). Automatic video system for aircraft identification. In *Proceedings of the Fifth International Conference on Information Fusion. FUSION 2002.(IEEE Cat. No. 02EX5997)* (Vol. 2, pp. 1387-1394). IEEE.

Liao, M., Shi, B., Bai, X., Wang, X., & Liu, W. (2017, February). Textboxes: A fast text detector with a single deep neural network. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 31, No. 1).

Shi, B., Bai, X., & Yao, C. (2016). An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. *IEEE transactions on pattern analysis and machine intelligence*, *39*(11), 2298-2304.

Lin, T. Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., ... & Zitnick, C. L. (2014, September). Microsoft coco: Common objects in context. In *European conference on computer vision* (pp. 740-755). Springer, Cham.

Pulli, K., Baksheev, A., Kornyakov, K., & Eruhimov, V. (2012). Real-time computer vision with OpenCV. *Communications of the ACM*, *55*(6), 61-69.

ICAO, Convention on Civil Aviation, 1981.

"Forming an N-Number". Faa.gov. 2015.

Circular, F. A. (2006). 150/5200-37. *Introduction to Safety Management Systems for Airport Operators*.

M. Farhadmanesh, A. Rashidi, and N. Markovic, "Implementing Haar Cascade Classifiers for Automated Rapid Detection of Light Aircrafts at Local Airports," in Computing in Civil Engineering, 2021.

M. Farhadmanesh, N. Markovic, and A. Rashidi, "An automated video-based air traffic surveillance system for counting general aviation aircraft operations at non-towered airports," Submitt. Publ., 2022.

M. Farhadmanesh, A. Rashidi, and N. Markovic, "An Overview of Aircraft Surface Movement and Operation Monitoring Systems in General Aviation and Commercial Airports," Submitt. Publ., 2022.

Farhadmanesh, M., Rashidi, A., & Marković, N. (2022). "An Image Processing Method for Light Aircraft Tail Number Detection in General Aviation Airports". *Transportation Research Board 101th Annual Meeting Transportation Research Board*, (TRBAM-22-02213)