# MPC-639
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**Project Title**

Automated Image-Based Aircraft Tracking and Record-Keeping for Utah Airports

**University**

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**Research Needs**

Transportation infrastructure, including highways, railroads, airports, waterways, and pipelines, need to be properly managed and maintained. To that end, engineers should be thoroughly aware of the current traffic load on each one of the above-mentioned transportation systems. They need the exact load of traffic in their transportation system in order to make necessary decisions and plan and act accordingly. Future planning can be adjusted by having an accurate estimation of traffic overload or underload. An accurate traffic control system also alters future resource allocations to address transportation systems' improvement.

Due to the extensive nature of the transportation systems, the need for an automated system to be able to calculate the traffic loads completely is inevitable. Currently, many of the highways and railroads are equipped with automated traffic control systems, such as vehicle counting and license plate recognition systems (figure 1). Big airway systems such as international airports and other large airports (e.g., commercial service airports, cargo service airports, and general aviation airports) carrying jet airplane traffic loads are equipped with the air traffic control systems provided by ground-based air traffic controllers to both direct the aircrafts and document their traffic load. <u>However, there is a lack of accurate traffic control systems in smaller sized airports, such as regional and local airports.</u>

*Figure 1 An automated vehicle counting system*

Traffic control is an essential measure for strategical airport management and maintenance. Having more precise data on the airport traffic, airport managers are one more step closer toward a secure airport environment. In this way, any small or big accident that occurs in the airport can be easily tracked and be inspected. In addition, knowing the exact amount of wheeled traffic (i.e., the number of small aircraft and large aircraft) going by in the airport helps the local and state's airport to plane for future construction and modification of the Airport Layout Plan (ALP), such as an extra runway, taxiway, and aircraft storage building, to meet the current airport needs. ALP could be adjusted too. Utah airport system consists of about fifty small to big sized airports. Figure 2 shows one of the airports in the State of Utah with different aircraft types that can land in this specific airport (i.e., Heber City Municipal Airport). According to the Federal Aviation Administration (FAA), each airport should be inspected for the pavement quality control biyearly. In the current practice, engineers do the in-field pavement inspection using manual data-collection or using aerial imagery collected by drones. In this approach, the current Pavement Condition Index (PCI) is determined (1).

Nevertheless, an exact traffic information of airports gives this opportunity to the engineers to predict the airport pavement condition too. A prognostic system is always ahead of a diagnostic system. This can directly be utilized in the future budgetary allocation to promote the airport's physical condition for its users.

*Figure 2 Heber City Municipal Airport*

Traffic management divisions can use the provided traffic data to determine if any airport capacity in the region meets the current traffic or an internal airport expansion is needed. In some cases building a new airport in that region might be the solution to distribute the traffic loads and avoid traffic concentration in one airport.

Except for a small number of airports that are equipped with traffic control towers, airports in the State of Utah are controlled in a traditional fashion. The current method relies on forms filled out by the pilots. In some cases, a rough number of the passed airplanes are counted using radio calls for landing permissions. However, these systems are highly prone to error and are not reliable. Also, there is no documented evidence after counting the airplanes using radio transmission data.

This project is an attempt to address the above-mentioned issue  by proposing an automated traffic control system in small-sized airports. An image-based traffic control system is one promising solution that is already in use for highway traffic control systems. In this system, we can monitor, count, and recognize airplanes flying from or landing in an airport. This can be achieved by using the video data collected from cameras mounted on strategic points in the airport. There are some motion-sensitive cameras which one might think can be used as an air-traffic control system; however, they are prone to over counting since usually there are many moving aircrafts in the taxiway areas which are normally close to the runway area. Using the collected video data and relevant computer vision techniques, we intend to build an air-traffic control system able to count the traffic load and to recognize the aircraft models flying from or landing on the airport's runway. We plan to try both feature-based machine learning method using a support vector machine (SVM) classifier and deep learning based methods for aircraft identification. More technical details about the proposed method will be provided within the next sections.

## Research Objectives

The objective of this research project is twofold:

1. Developing a computer vision-based air-traffic control system able to count and identify the airplane models within the Utah airports

2. Providing an overall framework for necessary hardware and software settings for aircraft detection and identification using computer vision techniques.

## Research Methods

The research method consists of two main frameworks:
1. Hardware framework
2. Software framework

The hardware framework consists of evaluating different types and resolutions of cameras (figure 3), data collection procedures, using existing visual data repositories in the airports such as security airport camera (figure 4). There are several possible locations for mounting the camera in the airports such as Fix-Based Operator (FBO) building and Precision Approach Path Indicator (PAPI) location at the airport. It will be depended on the runway length and width of the airport.


*Figure 3 Different camera types (left picture: BFS-PGE-27S5C-C PoE GigE Blackfly® S, Color Camera; right picture: The Autoscope Solo Terra)*


*Figure 4 An example of necessary hardware setting for a video capturing platform*

The software framework consists of two main steps:

1. Motion Detection
2. Aircraft Recognition

*Motion Detection:*

In this work, we investigate a vision-based aircraft motion detection algorithm that can be used in the design of our intelligent traffic control system. The input to the algorithm is video data obtained from a camera that is going to be mounted on a building in the airport. Motion detection using a stationary camera can be done by estimating the static scene (background). In this method, we read the frames of the video consecutively and compute their absolute difference. Next, a Gaussian filter is applied to the output, and then the result will go through a binary thresholding algorithm, which helps us to find better (dilated) contours. Motion detection and localization are used to reduce computational requirements. The results show that this method is able to reliably detect moving airplanes (in both landing and departure status) in the scenes captured from runways of the airports. Figure 3 shows the simplified motion detection framework flowchart.

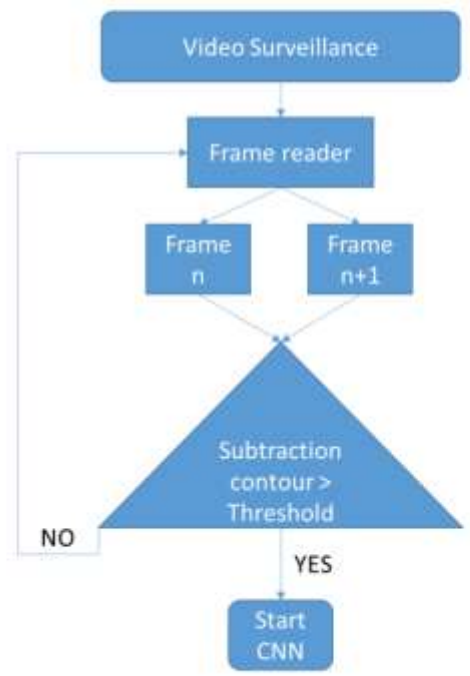


*Figure 5 Motion detection flowchart*

*Aircraft recognition:*

After detecting a moving object in the footage recorded from our camera in the airport, we need to know if it is an aircraft or not. In this step, we also recognize the aircraft model if the moving object was an aircraft. This aim can be achieved by two different methods: 1. Feature-based machine learning techniques; 2. Deep learning techniques. Two proposed approaches will be explained in the following.

*Feature-based machine learning techniques:*

Methods for aircraft recognition generally fall into either machine learning-based approaches or deep learning-based approaches. For Machine Learning approaches, it becomes necessary to first define features using one of the methods below, then using a classifier such as support vector machine (SVM).

Different image feature extraction methods:

- Viola–Jones object detection framework based on Haar-like features
- Scale-invariant feature transform (SIFT)
- Histogram of oriented gradients (HOG) features (2)

*Deep learning techniques:*

On the other hand, deep learning techniques are able to do end-to-end object recognition and classification without specifically defining features, and are typically based on convolutional neural networks (CNN).

The architecture of CNN is as follows:

**Step 1: convolution operation**

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters.

**Step 2: Rectified Linear Unit or ReLU (Activation) Layer**

In this step, the resulted output will go through the activation function, which is usually a linear function that is designed to compute middle layers (deep layers).

**Step 3: Pooling**

It is basically reducing the size of our image in the deep layers to save us from unnecessary computational expenses.

**Step 4: Flattening (full connection)**

Inevitably, in the last layers of our architecture, we need to have all the neurons (final image pixels) to be connected in order to be able to have a better prediction on the presented object in our image. Figure 6 demonstrates the configuration of the layers.

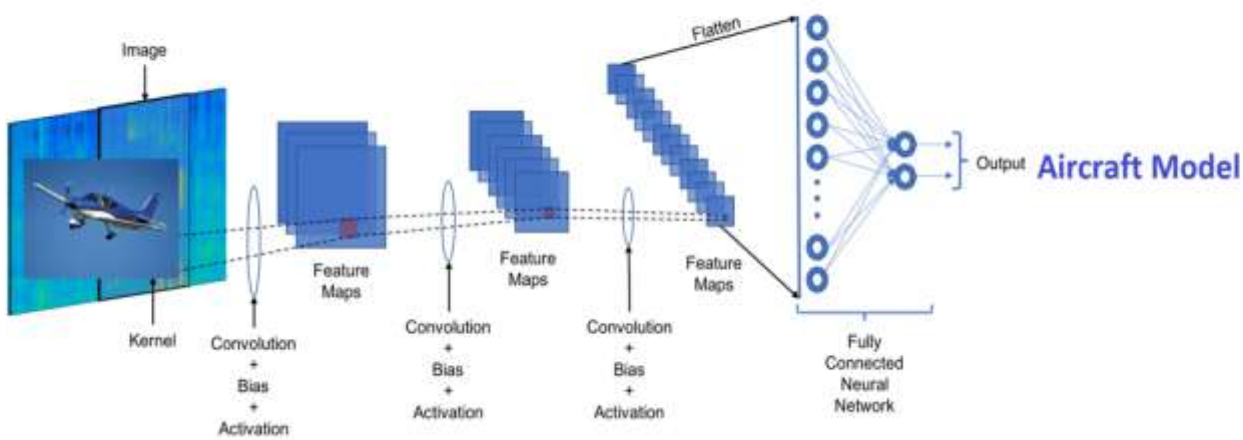


*Figure 6 Layers in a Convolutional Neural Network*

In order to enhance the accuracy of the Deep Networks, we need to adjust the architecture according to the problem situation, such as adding batch normalization layers and drop out options to avoid overfitting problems. Eventually, the design of a CNN suitable for the problem is the main goal in a vision-based object recognition (e.g., aircraft recognition) task. The following are some of the object detection methods in which their back-end is a CNN.

- Region Proposals (R-CNN (3), Fast R-CNN (4), Faster R-CNN (5), cascade R-CNN (6))
- Single Shot MultiBox Detector (SSD) (7)

- You Only Look Once (YOLO) (8)
- Single-Shot Refinement Neural Network for Object Detection (RefineDet) (9)
- Retina-Net (10)
- Deformable convolutional networks

**Expected Outcomes**

The expected outcomes for this project will include the following items: a hardware framework for adequately collecting videos from the runway at the airport; A software framework for adequately detecting and counting the aircraft traffic at the airport.

It is also necessary to mention that the outcomes of this project will be disscussed and evaluated by UDOT personnel as the practitioners who will be benefited from this project.

**Relevance to Strategic Goals**

Primary strategic goal: Safety

An automated detecting, tracking and record keeping system for aircrafts at small and medium size airports will eventually result in better managing the aiviation traffic and avoiding potential accidents, clashes, etc.

Secondary strategic goal: Economic Competitiveness

The proposed aircraft tracking and record keeping system will assit the decision makers to better plan for the traffic flow at airports, better assign resources, avoid high volumes of traffics and improve the economical performance of airports.

**Educational Benefits**

The PIs of this project are currently teaching two graduate level class called "CVEEN 6790: Advanced Computer Aided Construction" and "CVEEN 6530: Quantitative Methods for Transportation Operations". It is expected that the developed algorithms, methods, and case studies in this project will be directly converted into new course materials for these courses. In addition, a number of selected undergraduate and graduate students will be participating in different steps of this project including data collection, processing, and validating the obtained results.

**Technology Transfer**

The technology transfer process for this project will take place through two major channels: 1) publishing (presenting) research results in scholarly journals (conference proceedings); and 2) direct interactions with UDOT personnel as the potential end users for the results of this study.

**Work Plan**

The project will include the following major tasks:

1. Literate review and initial evaluation of the existing photogrammetric software packages; Expected completion date: end of 2$^{nd}$ month
2. Developing necessary hardware settings and selecting case studies; Expected completion date: end of 5th month
3. Conducting experiments, and data collection; Expected completion date: end of 8th month
4. Processing data and generating results; Expected completion date: end of 11th month

5. Preparing the final report; Expected completion date: end of 12th month

**Project Cost**

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|---|---|
| Total Project Costs: | $63,001 |
| MPC Funds Requested: | $28,000 |
| Matching Funds: | $35,001 |
| Source of Matching Funds: | Utah Department of Transportation, financial support |

**References**


[1] FAA Airport Data (Form 5010) from National Flight Data Center (NFDC), also available from AirportIQ 5010

[2] Dalal, N., & Triggs, B. (2005, June). Histograms of oriented gradients for human detection. In *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)* (Vol. 1, pp. 886-893). IEEE.

[3] 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).

[4] Girshick, R. (2015). Fast r-cnn. In *Proceedings of the IEEE international conference on computer vision* (pp. 1440-1448).

[5] Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems* (pp. 91-99).

[6] Pang, J., Chen, K., Shi, J., Feng, H., Ouyang, W., & Lin, D. (2019). Libra r-cnn: Towards balanced learning for object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 821-830).

[7] 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.

[8] 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).

[9] Zhang, S., Wen, L., Bian, X., Lei, Z., & Li, S. Z. (2018). Single-shot refinement neural network for object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4203-4212).

[10] Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision* (pp. 2980-2988).