Just a T.A.D.
Final Design Review Report

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***Abstract*—Unmanned aerial vehicles (UAV or drone) provide an effective way to get expensive or otherwise inaccessible images and video. This type of data is especially important for traffic analysis as the top-down view from a drone is ideal for gathering data about traffic. Just a T.A.D. (Traffic Analysis Drone) is a road traffic monitoring system that provides a system for capturing and analyzing video. The system uses a drone camera to capture top-down videos of traffics and performs image processing to extract traffic data such as density and interval between cars in a lane. The data is communicated to a data server, and a web interface is available to easily access the data.**

Index Terms – Image Processing, Traffic Analysis, Unmanned Aerial Vehicle

I. INTRODUCTION

TRAFFIC IS A MAJOR ISSUE FOR SOCIETY AND IS ONLY PROJECTED TO INCREASE. The roadways are regularly filled with cars being used to transport goods and people. Traffic is just a part of life for the average person. In 2014, commuters had an average of 42 hours per year in delays, and very large urban areas (regions with over 3 million people) can have commuters with average delays of up to 82 hours per year [1]. These delays result in wasted man hours and additional costs for operating vehicles. Workers need to plan their daily commute with expectations of delays due to traffic. Truck drivers will encounter even more traffic as they spend their work hours on the road. In addition to consuming man hours, the delays result in increased consumption of fuel, which results in additional costs. The direct cost of fuels and indirect cost of man hours resulted in $160 billion in losses [1].

Their costs are only projected to increase as more cars fill the roads. This is primarily due to the growing economy, workforce, and population. These factors will result in more cars and trucks on the road, resulting in more congestion on the already full roads. The response to the growing traffic has been inadequate as infrastructure are unable to meet the demands of the traffic. By 2020, the total delay time will increase by 1.4 billions hours, totaling 8.3 billion hours in traffic [2]. And, this will result in $192 billion in losses due to congestion, which was $160 billion in 2015 [2]. If this issue is not resolved or slowed, congestion will only continue to grow, and Americans will pay the price with their time and money.

However, a solution is not so simple as building more road infrastructures. These solutions need to be based on data that ensures that there will be less traffic in the area, not just moving the traffic to a new road. Knowing where traffic occurs will help with deducing why it is occurring there and how to best tackle that space. The issue comes with how this data is collected. Current data collection methods primarily capture two types of traffic sensors: “mobile sensor data” and “point sensor data” [3]. Mobile sensor data is similar to google maps as it can capture the data of a single car via GPS, and point sensor data is based on a stationary camera recording cars in a small area [3]. These methods are inadequate as not all cars can be captured in point sensor data and mobile sensor data requires that most cars have the application available. Point sensor data is collected via stationary cameras on the road. These cameras can be easily obstructed and only provide a small sample of the larger traffic picture. Mobile sensor data is primarily done by Google Maps and GPS data from cars. For mobile sensor data to be useable for traffic engineers, almost all cars on the road would need to be recorded [3]. Mobile sensor data and point sensor data are not able to provide the necessary information needed for ideal traffic analysis.

Just A T.A.D. will be able to provide the third type of sensor data: “space sensor data.” Space sensor data is able to provide data about all cars in a large space, such as speed, density, etc and is largely considered to be the most ideal in traffic analysis [3]. T.A.D. will utilize a drone with a bottom-mounted camera to capture video. The video is then processed to provide necessary information based on the space sensor data of the video. Cars are detected and their count and space between cars in a lane (interval) can be measured. The processed data is then sent to a data server where a web browser can be used to access and view the data.

This data is useful to transportation engineers as it gives them data about the traffic situation in an area, and they can formulate a solution based on the data provided. The space sensor data provided is normally hard to obtain. It usually entailed using a helicopter to capture videos of traffic, which then needs to be further processed. Due to the cost associated with this collection method, cameras collecting point sensor data are preferred. T.A.D. will provide not only a means of

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collecting space sensor data but also provide analysis of that data. In addition, by using a drone, the general cost of obtaining is comparatively cheaper.

Traffic engineers will be able to use T.A.D. to improve traffic conditions by having the necessary data needed to make decisions. The possibility of less traffic on the roads will mean a better economy as people and goods will reach their destinations sooner. This also means businesses will encounter lower losses Despite these benefits, the unintended consequence is the drone's surveillance capabilities. The drone will be able to collect a substantial amount of video data. Although, traffic cameras already collect a substantial amount of video data, a drone is able to fly anywhere and record data. It is important that the public understands that it is only for traffic data. More concerns will be raised if T.A.D. is used in residential areas as it would have homes in its field of view.

II. Design

A. Overview

T.A.D. is a video capture and analysis system that utilizes a drone to obtain top-down video of traffic to be used for processing and analysis. The general system can be applied to any drone where the module will fit. It consists of a Raspberry Pi computer with a camera. The drone is operated manually and primarily acts as a medium for transporting this module.

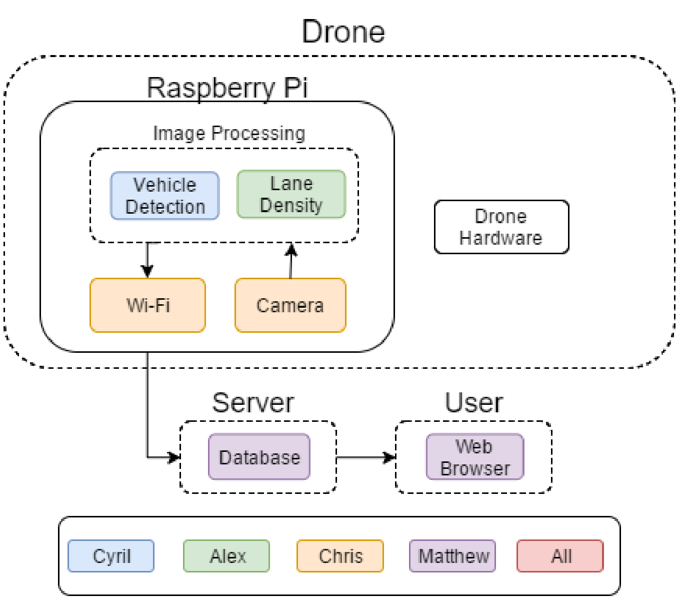


Fig 1. General block diagram of TAD System

The block diagram, displayed in fig. 1, shows the main components of the T.A.D. system. The drone block consists of a Raspberry Pi and the drone hardware. The drone itself is not necessarily part of the design but does allow for additions, if needed. The drone will be controlled manually in this proof of concept, but can also have pre-planned flight paths for autonomous flight. The Raspberry Pi consists of the a camera and image processing software. The camera is used to provide video to the image processing. The image processing is primarily concerned with car count and density of the video.This is done through image processing techniques that will be described in detail in a later section. Only the car count and density are sent to the database. The video itself is not sent as all the necessary data can be calculated on the Raspberry Pi and that data can be sent to the server. This data is sent via Wi-Fi. Once the data is in the database, a web browser can be used to access it. Data is refreshed every 5 seconds, and it can be viewed and downloaded.

The design alternatives were primarily related to where the image processing would be done and how it would communicate the results to the server. Initially, the video was going to be sent to the server, where it would be processed. This provided more flexibility with the processing power needed for the algorithm. However, the final decision was to have the image processing on the Raspberry Pi as transmitting video was infeasible with the earlier goal of 3G. Wi-Fi was the final choice as the 3G component could not be finished. This requires the drone to have Wi-Fi access in order to transmit the processed data to the database.. Additional traffic analysis data can be calculated, but would require additional time and more processing power. A GUI could also be available on the web browser, but would require additional work with integrating a GPS.

Table 1 lists the specifications set forth at the point of MDR and includes portions that will be realized upon completion and integration. The flight time and payload specification is based on the drone used. In addition, flight time includes the drone flying to the desired observation point. The altitude displayed is the one used during development and provided a balance of car size and view of the road.. The browser refresh rate is current setting at which the web site will refresh its tables to display any new traffic data..

SYSTEM SPECIFICATIONS

Specification	*Value*
Flight Time	15 minutes
Altitude	40 m (131.2 feet)
Autopilot	Available
Payload	< 3 ounces
Range	1 km (0.621 miles)
Browser Data Refresh Rate	5 seconds

Table 1. General T.A.D. system specifications

B. Block 1: Raspberry Pi Modules

The Raspberry Pi Modules are made up of both the Arducam OV5647 Video Module (camera) [4] and the Huawei E353 3G USB Wireless Modem (3G dongle) [5].

Both of these will be connected to and interfacing with a Raspberry Pi, similar to the one shown below.

Fig 2. Raspberry Pi, compact computer used for educational purposes

The dongle weighs less than 1.05 ounces and has download speeds up to 150Mbps. Since we chose AT&T as our data provider, the dongle should provide internet wherever AT&T has service.

Fig 3. Huawei E353 3G USB Wireless Modem

The camera weighs 0.3 ounces and is capable of taking photos in resolutions ranging from 480p to 1080p depending on the configuration. At two meters, its field of view is 2.0m x 1.33m. The camera's angle of view is 54 x 41 degrees.

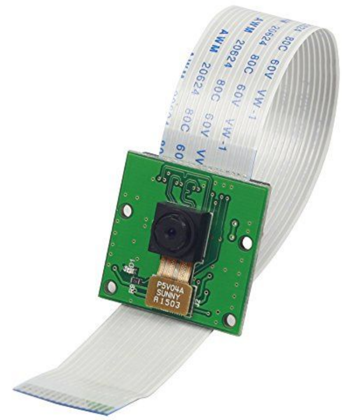


Fig 4. ArduCam, interfaces with the Raspberry Pi to capture video

The camera is controlled by the Raspberry Pi and captures frames at regular intervals to create a video. While capturing the footage of a road, the Raspberry Pi is also processing each frame of the video to obtain our data(See Block 2 for Image Processing). Then, the 3G dongle was supposed to be used to communicate the results from the Raspberry Pi to our database. Unfortunately, this was not achievable.

Before being able to record video, the Raspberry Pi had to be interfaced with the ArduCam. The Raspberry Pi, at first, wouldn't recognise the ArduCam upon plugging it into the camera interface, so the camera's initial setup lasted a few hours. The cause of this problem was a loose connection in the ArduCam's hardware. Applying pressure to the connections on the camera allowed for it to be recognised by the Raspberry Pi.

The ArduCam was then programmed by using the PiCamera library in python. We then mounted the Raspberry Pi and camera onto the drone for testing. Our program was developed so that the camera has a fixed delay before it begins taking video. This is to account for the time needed by the drone to take-off and fly to the desired nearby location. After the drone is in place and the delay ends, the Raspberry Pi begins taking video and processing each frame as it's captured. This will be further described in the Image Processing Portion(Block 2).

In attempt to achieve networking via the 3G connection, the Raspberry Pi also needed to be interfaced with the Huawei E353 USB Wireless Modem. After plugging the dongle into the Raspberry Pi, it was immediately recognised as a USB device. This was as expected because it was in USB mode, but needed to be changed into the modem mode for it to begin transmitting data. After many hours of testing and researching, a program called USB Modeswitch allowed us to achieve this. This program requires a file to contain the Huawei E353's specific ModeSwitch identity, a very lengthy number found online after many hours of research. This allowed the Raspberry Pi to switch the dongle into modem mode so that it may begin transmitting.

The next step was to configure the dongle so that it may use the SIM card and connect to AT&T's 3G network. WVDial, PPP, and sakis3G are USB 3G configuration libraries that were used in attempt to connect the dongle to AT&T's network.. After none of these fixed our problem, further troubleshooting showed that the dongle was being recognised as a network interface. Therefore, we attempted to ping various known websites and received responses. It was later determined that these responses were from the dongle itself instead of the actual web servers. We could only ping the dongle and not anything beyond that.

It appeared now that the dongle was acting like a router without a DNS service. We manually updated the dongle's routing tables in attempt to circumvent this problem, but that still did not help our situation.

After much more troubleshooting, we were unable to connect the 3G dongle to AT&T's network, but two final possible solutions were found.

First, the LED on the dongle was flashing in a manner that means it cannot find the network. Therefore, the dongle might not be connecting because it doesn't have AT&T service in the areas we have been testing. We were only able to test different areas based on whether a cell phone could connect to AT&T's network. Since the antennae on cell phones are different from that in our dongle, we cannot conclude that because a cell phone has service, the dongle does also. The dongle appears to have never been in range of AT&T's network. If redoing this project, we would try using a different service provider to remedy this.

Second, we came across multiple times in our research that the Raspberry Pi's USB ports might not output enough power for the dongle to perform correctly. To fix this, others have used an external, powered USB hub. Unfortunately, this would be too much weight for us to mount on our drone, so this fix is infeasible.

In the end, we were able to successfully use the ArduCam as desired, but we were unable to implement the Huawei E353 3G USB Wireless Modem into our final project design.

Past skills which have aided us in our work include, but are not limited to: Programming, Networking, and Hands on Lab courses.

C. Block 2: Image processing

This block (Fig. 1) consists of the majority of the novel engineering work. The broad goals of this block is: given the video feed from the drone's onboard camera, find the cars in any given frame on a chosen road, the spacing between cars in each lane on a chosen road, and the density of cars. The spacing is defined by the distance s_i between cars[3]:

$$s_i = x_{i-1} - x_i$$

The density k is defined by the number of vehicles N observed on a unit length of road L [3]:

$$k = N/L$$

With some tolerance for error with regard to the incomplete spacing of the first and last vehicles, we can restate L as the sum of the spacings between cars [3]:

$$L = \Sigma^{N}_{i=1} x_i$$

Now that we've defined our goals, we can proceed to our approaches and solutions to problems encountered.

We used OpenCV as a starting point, as it is a widely used computer vision library which is cross-platform capable because it uses Python. This allows us to develop code on our main computers and be reasonably sure that the code will work on the Raspberry Pi.

Early on, the group decided that a stationary, purely top-down perspective would generate the simplest data, considering distortion from perspective and optics. This top-down data would also make the calculation of spacing and density simpler, as we would need to account for trigonometric distortion of spacing and density less as well, as in Fig. 2.

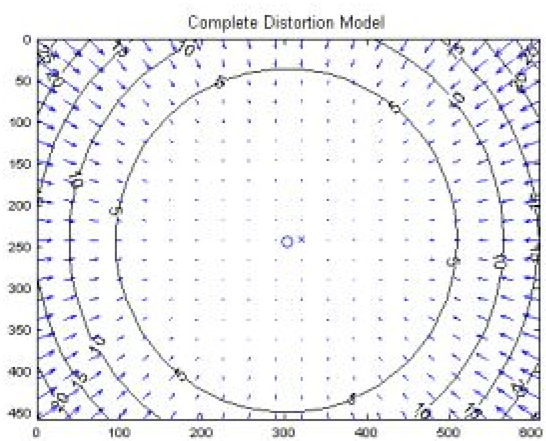


Fig 5. This demonstrates the distortion seen by a camera due to optical and perspective effects. The center of the image is relatively undistorted, but near the edges what should be dots on a grid can be seen as rays at an angle [6].

At first, our attempts were primarily naive approaches using built-in tools in OpenCV, such as edge detection[7] or built-in background subtraction [8]. Simple Canny [7] edge detection was not a viable approach as for any given image, there was too much noise to reliably detect a car versus the pavement, and it was exceptionally sensitive to car color. Background subtraction was more generally more accurate than edge detection in our stationary camera test cases, but even slight movement would make the camera background subtraction fail completely, which is a concern for .

Thresholding[9] was another naive approach, but it was relatively difficult to pick a thresholding value that did not exclude a significant number of cars in a particular test image, and it would have to be adjusted to local lighting conditions. Even then, in our available test videos, the resulting detection rate was not as high as would be preferable for the trial-and-error involved in picking threshold values.

The lack of reasonable test data was an issue early on, as it made it difficult to determine if our methods were failing due to variables that were irrelevant in our chosen data collection method. For example, we were unable to find traffic data from an overhead stationary drone, and we made due with data collected from a moving drone [10], and data collected from stationary cameras overlooking overpasses [11][12]. This data makes it difficult to account for factors such as lense viewing angle, and for the latter two videos, the angled view prevents an easy calculation of spacing, and by extension, density.

The final, chosen approach took into account the fact that background subtraction was an accurate method of determining motion for a stationary camera. By taking a frame of the video feed every 1/6th of a second, and mapping previous frames onto the most recent frame, we can approximate the effect of a stationary camera, masking all images by the area that would not be visible in the projections for simplicity's sake. Then the newly projected images are fed into a background subtraction algorithm. Since each projection does not take into account the motion of individual cars within the image, then the background subtraction "sees" the cars as moving while stationary objects in the frame do not move. We will now walk through each step of this algorithm in more detail.

Fig. 6. An individual frame of the video [10].

Fig. 3 is one frame of a video used for testing. Subsequent frames are taken at intervals of 1/6th of a second, or 10 frames, to allow for enough movement between frames. These frames are put on a queue of fixed length to use in the rest of the algorithm.

The algorithm used to match images is called SIFT, for Scale Invariant Feature Transform [13].

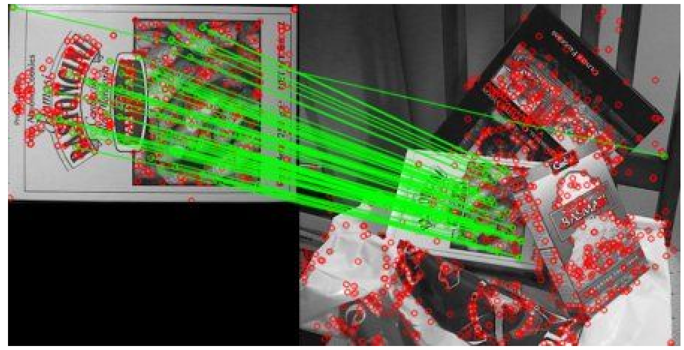


Fig. 7. An example of feature matching in a busy environment [14]

SIFT (as shown in Fig. 4) works by convolving the image with a variable scale Gaussian function in *x* and *y*, finding the differences between the various scales, then finding the extrema of these differences to get keypoint descriptors of an image that are invariant to scaling, rotation, and location. Thus, these keypoints in one image can be matched with keypoints in another. SIFT was chosen because it is integrated with OpenCV, allowing us to focus on the larger parts of the algorithm.

Now that the key points for each image have been found, we can find the homography matrix that maps each pixel from one image to the other [6]. A homography matrix is a 3x3 matrix that maps lines to lines, and it is defined by the following relation (where x_1 is the x coordinate in the image, x_2 is the y coordinate, and x_3 is affected by nonplanar motion):

$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

Furthermore, the structure of H affects what properties the transformed image has, such as representing a rotation or a scaling, but for the most part they are irrelevant to our algorithm. This is illustrated in Fig. 5.

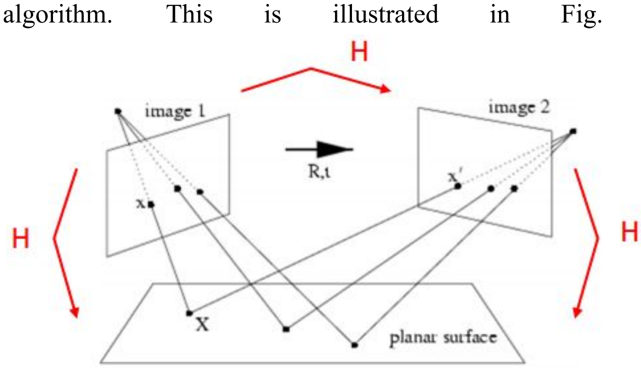


Fig. 8. A graphical explanation of how homography matrices change points in one perspective, the first image, to points in another perspective, the second image [6].

Again, OpenCV provided pre-written code to estimate the homography matrix and apply it from one image to another.

To compensate for the fact that the projected image does not cover the entirety of the newest image (as the drone is moving), a blank mask is also warped by the homography matrix and is combined with a bitwise and operator of previous masks. This mask will be applied over each frame to be fed into the background subtractor. This will ensure that the background subtractor does not see extraneous detail.

The background subtractor is based on the paper “Improved Adaptive Gaussian Mixture Model for Background Subtraction” (Zivkovic, 2004) [15]. This algorithm uses a per-pixel estimation of whether the pixel is part of the background (stationary) or part of the foreground (moving) by a recursive methodology. It is relatively responsive to changes in illumination, and can also estimate whether a change in a portion of the background is actually just a shadow from a foreground object. OpenCV also provided access to and implementation of this algorithm. This background subtractor provides the estimated background as a binary mask, where foreground is white and background is black. After background subtraction, we perform opening transformation on an image [16] to remove noise using a 3x3 kernel. An opening is image erosion followed by dilation. Erosion is a transformation where the kernel “slides” over the image (as in image convolution) and if the area under the kernel centered at a particular pixel does not only contain white pixels, then that pixel is turned black in the resulting image. A dilation does the opposite, if any pixels are white under the kernel centered at a particular pixel, then the pixel is turned white in the resulting image [16].

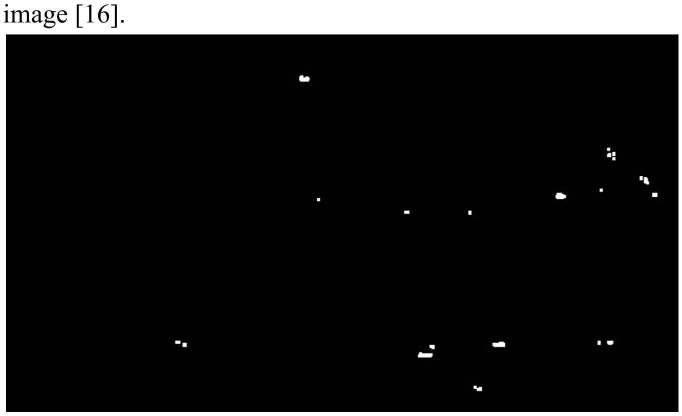


Fig. 9. The output of our background subtraction.

This output (shown in Fig. 6) is given to OpenCV’s contour detector [that thing]. This gives us a point description of detected contours, and we can use that to find motion, and presumably cars. This allows us to find Fig. 7.

Fig. 10. Detected motion. As you can see, there is some noise and false positives, but on the whole it detects motion accurately. (The far left of the screen falls under the mask mentioned above.)

This algorithm fails for stationary cars, but it is reasonably responsive to poor camera conditions in most of our test cases. In this particular case it detected 28 out of 30 cars in the lower highway, or 93%.

While the previously used algorithm was effective under poor conditions, it was not feasible to use this algorithm on the Raspberry Pi, as it was very computationally expensive. This algorithm may be useful in the context of a video stream, where a mainframe could spend arbitrary amounts of computing power on it, but this approach was outside the scope of our MDR-designated design. As such, we created a new, lightweight algorithm that could run in real-time on the Raspberry Pi. It used some simple, statistics-based heuristics to gauge whether a pixel was “strange,” and if there were a cluster of strange pixels in the location a car would be expected (i.e., the road), then we declare the clustering to be a car.

As a pre-flight measure, we use outside tools (in our case, Google Maps and the accompanying Mission Planner software for the 3DR IRIS, but any sufficiently detailed map would suffice) to find the compass direction of the road, as well as a GPS coordinate directly above the road. By orienting the drone along the road, and using GPS to direct it directly above the center, we can we can find the center of the desired lane using simple trigonometry. Apparent distance in the camera’s view is inversely related to height of the drone, which can be controlled.

The method that the new algorithm uses is much less computationally expensive, so it can be feasibly used on the Raspberry Pi. Once the location of the lane is known (described above), we iterate over a line of pixels expected to be in the middle of the lane to find both the mean and standard deviation of the pixels’ values. We then iterate over the line of pixels again, and see when a pixel’s value minus the mean is greater than the standard deviation. This is how we label a pixel “strange.” When we have a collection of strange pixels nearby each other, with some tolerance for not-strange pixels in between, we declare this to be a car.

This also has the advantage of functioning in traffic jam situations, which the previous algorithm does not do. Unfortunately, the new algorithm is significantly less accurate than the previous algorithm, particularly with regards to false positives. The new algorithm only has an 80% success rate in our tests on average, with some cars being detected 100% of the time and some cars being detected 60% of the time. Like the previous algorithm, this discrepancy is the result of some cars being a very similar shade to the road in gray scale. Fig. 8 shows a successfully identified car, and Fig. 9 shows a false positive due to the road itself being cracked. To mitigate this somewhat, we put a minimum number of frames a car could be detected before being identified positively as a car. This cut down on random noise

Fig. 11. A successfully identified car, shown here as green pixels

Fig. 12. A false positive. Here, part of the road is cracked significantly more than other sections of the road, so the cracks are assessed to be cars.

The two factors above combine to form the following density graph (Fig. 10)

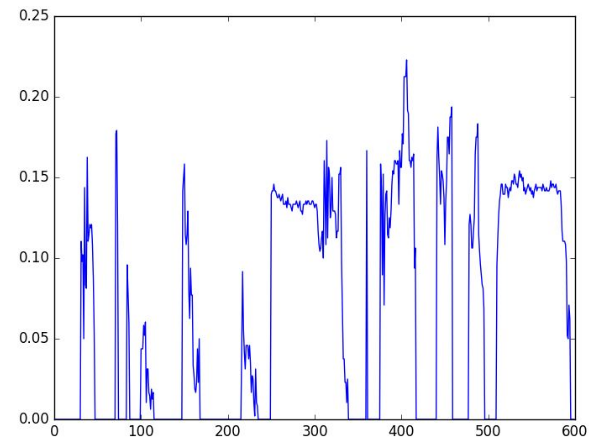


Fig. 13. The recorded traffic density of 20 seconds of a test flight.

As you can see, the false positive rate does make the true presence of a car difficult to objectively determine.

For future directions of the project, I would consider machine-learning, classification based approaches, as we did not fully consider them at the start due to having no test images.

D. Block 3: Data Server and Web Browser

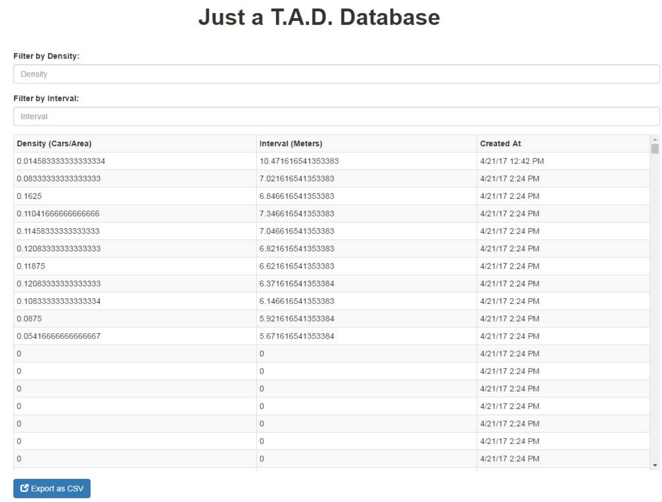
This block represents the implementation of the data server and web browser. From a high level point of view the processed data from the Raspberry Pi would be transmitted to the data server via 3G. The data, primarily car density and interval (spacing between cars), would then be sent to the database by the 3G dongle. The web browser would then query the database and provide the end user an easy to use and more aesthetically pleasing UI. That being said the goal of this block is to implement this system from the backend (database) to the web browser (frontend) utilizing the MEAN stack of web development. The MEAN stack represents the technologies utilized in this popular branch of web development which are mongoDB, ExpressJS, AngularJS, and NodeJS [18].

Starting from the bottom-up, the database is hosted on mongolab, a cloud based database host [19]. The primary benefits to hosting the database on the cloud rather than on the Raspberry Pi is to take as much processing load off the Raspberry Pi as possible due to the intense image processing already taking place on it. This would be more beneficial as opposed to running the image processing on a server as transmitting images over 3G would most likely cause bandwidth issues. The hosting service is also free up to 500 MB at any given time which should be more than enough as only numbers are being stored. In addition, mongolab also provides a low level visualization of the database content for manual entries which aids developers as well as connection information to the database either by the shell or mongoDB URI for smooth integration into the code involving data transmission over 3G. The database itself utilizes mongoDB, a NoSQL database system that stores its contents as JSON documents which allows for varying structure [20]. This allows for dynamic schemas meaning the parameters and variables setup in the initial database implementation can be changed at anytime. This flexibility favors all phases of this project from development and testing to final staging as a database bottleneck is not present.

In order to connect the backend (database) with the frontend, middleware and server side technology is required. ExpressJS and NodeJS are both backend technologies that will enable this connection and framing of the web application with the database. NodeJS is a lightweight backend runtime environment used to build the raw components of the web application in terms of server side activity such as connections to the application [21]. The aforementioned connections also include the connection to the database which utilizes its own driver for mongoDB Driver API [22]. ExpressJS works in hand with NodeJS by creating the framework for the web application. More specifically, routes are created in which any type of HTTP request to/from the web application will need to be redirected by ExpressJS in order for the web application to service said requests as seen in this example in the ExpressJS 4.X API [23].

With the backend setup, the final implementation of the MEAN stack is AngularJS. AngularJS can be thought of as an extension of HTML in which it allows for dynamic views as HTML in its core was made for static views in terms of web pages. AngularJS allows for non intrusive implementation of this technology with its dynamic front end framework [24].

The web app has been updated to be more user friendly by automatically updating the data table shown. It does this by polling the mLab database every 5 seconds so that the most recent data would display at the top of the table. The table also features infinite scrolling so that the user would not have an expanding web page to constantly scroll down as data fills up in the table. The table headers are also clickable which allow the user to sort in increasing/descending order based on the column header they have clicked. Also, a specified density/interval value can be queried through the search boxes should the user require to do so. Finally, an export as CSV button was implemented in which a user would be able to click it and a .csv of the data currently in the database would be downloaded instantly. This allows a traffic engineer to obtain raw data they require to perform analysis, custom calculations, etc. instead of having to rely on a graph. Basic programming knowledge from ECE 242 Data Structures & Algorithms and exposure to databases from ECE 373 Software Intensive Engineering applies to work done in this block.



Density (Cars/Area)	Interval (Meters)	Created At
0.014583333333333334	10.471616541353383	4/21/17 12:42 PM
0.08333333333333333	7.021616541353383	4/21/17 2:24 PM
0.1625	6.846616541353383	4/21/17 2:24 PM
0.11041666666666666	7.346616541353383	4/21/17 2:24 PM
0.11458333333333333	7.046616541353383	4/21/17 2:24 PM
0.12083333333333333	6.821616541353383	4/21/17 2:24 PM
0.11875	6.621616541353383	4/21/17 2:24 PM
0.12083333333333333	6.371616541353384	4/21/17 2:24 PM
0.10833333333333334	6.146616541353383	4/21/17 2:24 PM
0.0875	5.921616541353384	4/21/17 2:24 PM
0.05416666666666667	5.671616541353384	4/21/17 2:24 PM
0	0	4/21/17 2:24 PM
0	0	4/21/17 2:24 PM
0	0	4/21/17 2:24 PM
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Fig. 14. Just a T.A.D. web application

III. Project Management

Project Status at Completion

Goal	*Completion Percentage*
System Integration	90%
Interval Spacing	100%
Camera and 3G	50%
Database and Web UI	100%

Table 2. Final Components and level of completion

The MDR goals are displayed in Table 2, above. These goals were largely completed: car counting, interval spacing, and database and web UI. The only goal that had issues was the 3G portion of the Raspberry Pi block. This was largely due to complications with establishing the 3G. Other than the 3G, all subsystems are integrated and Wi-Fi was used in place of 3G for communication to the server..

Our team meets weekly with our advisors, Professor Hossein Pishro-Nik and Professor Daiheng Ni (CEE).. We also meet separately as team to talk about individual work and how we will integrate our pieces for the final design. We also meet when ordering parts. The image processing was primarily handled by Alex. Alex handled image processing for detecting intervals between cars and developing algorithms to offset camera movement. Cyril assisted with integration of the components. He provided the code needed to communicate data to the server and the code needed to feed camera data directly to the image processing. Chris was responsible for the Raspberry Pi and its modules. This included setting up the Raspberry Pi's 3G attachment. Matt was responsible for the data server and creation of the web page that displays the data from the drone. In addition to each member's individual components, all team members were responsible for completion of the project and assisted each other when necessary.

Better time management was needed as not all components were integrated and completed at the time of FPR. In the end, the 3G portion of the project could not be completed. This was a result primarily due to poor time management and required more support from the group as a whole. However, further integration was done between FPR and demo day. All subsystems except 3G were integrated with each other and provided a system that could process images from the live camera feed and then send the processed data to the server via Wi-Fi.

IV. Conclusion

Our team accomplished most of our goals since MDR, but encountered issues with the 3G module. We did not expect this component to have as many issues as it did. In addition, the sim card was delayed and further postponed implementation of this overall block. The other blocks of the project were completed and integrated. Wi-Fi was used for communication of the processed data from the Raspberry Pi to the server. Overall the project did not meet its original goals, but significant progress was made which allowed for all components to be completed and integrated except for the 3G.

The majority of the project is completed and integrated together except for the 3G. The image processing block is able to get an accurate car count and interval about 80% of the time. The Raspberry Pi block contains the image processing and provides integration between the camera and image processing. Instead of 3G, Wi-Fi is used to communicate image processing data to the server block. The server block contains the database and refreshes every 5 seconds to update the displayed data. In addition, a .csv file is available for download. The drone can be controlled by autopilot or with the remote controller. Telemetry data can be recorded by connecting the Iris 3DR+ USB antenna to a phone or computer to log the location, altitude, and direction of the drone.

Appendix

A. Application of Engineering

Just a T.A.D. involved the use of many engineering concepts as well as math and some civil engineering. The primary concepts involved in the project were data structures and algorithms, image processing, and traffic analysis concepts. The project was largely software based as the team consisted of four computer systems engineering majors. The image processing and Raspberry Pi integration code was written in Python. The data server and web browser were largely written in languages used in the MEAN stack of web development. Exposure to these languages are outside the scope of engineering classes. However, the basic concepts of programming and software development were used and taught in coursework from ECE 242, ECE 373, and ECE 570. Traffic analysis concepts were also learned in order to understand measurements for interval. Professor Ni provided his textbook and consulting in this matter. Much of the image processing and web development were learned during the process.

B. T.A.D. Cost

Below is the cost of the project in terms of development and production cost. However, the majority of the components cannot be bought in bulk. In addition, the drone used in development was provided by Professor Pishro-Nik. The costs are shown in table 3.

Development		**Production**	
Part	Cost($)	Part	Cost($)
Drone	Free*	Drone	598.00
Raspberry Pi	49.99	Raspberry Pi	49.99
Raspberry Pi Battery	16.99	Raspberry Pi Battery	16.99
Camera Module	14.99	Camera Module	14.99
Huawei 3G Modem	33.99	3G Dongle	33.99
3G Subscription	25.00	3G Subscription	25.00
USB cord	5.00	USB cord	0.41
FAA Registration	5.00	FAA Registration	5.00
Total	**150.96**	**Total**	**744.37**

Table 3. Cost of Just a T.A.D.

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