Statistical profile generation of real-time UAV-based traffic data

Anuj Puri
University of South Florida

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Statistical Profile Generation of Real-time UAV-based Traffic Data

by

Anuj Puri

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
Department of Computer Science and Engineering
College of Engineering
University of South Florida

Co-Major Professor: Kimon P. Valavanis, Ph.D.
Co-Major Professor: Dmitry Goldgof, Ph.D.
Chris P. Tsokos, Ph.D.
Ed Mierzejewski, Ph.D.
Pei-Sung Lin, Ph.D.

Date of Approval: August 28, 2008

Keywords: traffic analysis, simulation modeling, intelligent systems, unmanned aerial vehicles, traffic forecasting.

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Statistical Profile Generation of Real-time UAV-based Traffic Data

Anuj Puri

ABSTRACT

Small unmanned vehicles are used to provide the eye-in-the-sky alternative to monitoring and regulating traffic dynamically. Spatial-temporal visual data are collected in real-time and they are used to generate traffic-related statistical profiles, serving as inputs to traffic simulation models. Generated profiles, which are continuously updated, are used to calibrate traffic model parameters, to obtain more accurate and reliable simulation models, and for model modifications. This method overcomes limitations of existing traffic simulation models, which suffer from outdated data, poorly calibrated parameters, questionable accuracy and poor predictions of traffic patterns.
Chapter 1

Introduction

1.1 Motivation

The increase in number of vehicles on roadway networks has encouraged transport management agencies to allow use of technology advances and innovative solutions to obtain data on traffic trends and to monitor and control traffic in real-time.

The motivation of this particular research comes from the fact that current approaches for obtaining traffic data are expensive, highly man-intensive, and lack spatially. Moreover, traffic planners rely on simulation models that currently are poorly calibrated due to lack of sufficient and “good” traffic data. Thus, the proposed approach may be used to collect real-time data and to obtain substantial detailed information which can prove beneficial to traffic planners who will make informed decisions.

Small, unmanned helicopters offer a novel, viable and cost-effective solution to the problem of collecting spatial and temporal real-time, dynamic, video-based traffic network data. A team of small tele-operated / semi-autonomous unmanned helicopters, each equipped with a fully autonomous pan-tilt camera vision system may be used to: track individual vehicles; track the fastest moving captured vehicle; ‘lock in’ a specific vehicle dictated by a human operator who views dynamically obtained and processed video data; provide vehicle counts; monitor traffic over an intersection, or road segment, or specific traffic network; evaluate and assess traffic patterns, and improve traffic management. Most important of all, this system may be used for emergency
response scenarios where helicopters may fly to the scene of an accident in least time and provide visual data to emergency response team who can then make timely informed decisions. In short, aerial vehicles may be used for traffic data collection and surveillance.

1.2 Problem Statement

This research focuses on the ability of custom-made unmanned helicopters to spatially collect data, use this data to obtain traffic patterns and be able to predict future trends pertaining to the traffic network. In case of incidents/events, traffic conditions over the affected network may change significantly with time thus, requiring immediate actions. Time-varying parameters such as queue length, delay and speed are difficult to project using existing simulation models. Moreover, these simulation models are calibrated using historical data, thus, their precision and accuracy is questionable. The problem statement is multi-fold and can be expressed as follows:

• Data collection and methodology:

Current data collection approaches tend to provide only count-based information using stationary devices such as loop detectors embedded in pavements or video cameras mounted on poles. This data is hard to collect and lacks the advantage of spatiality because it only covers a certain segment of the network.

• Calibration and update of simulation models:

Currently, a simulation model is calibrated using limited amount of data. Although current simulation models have the ability to model complex traffic behaviors, models are typically calibrated based on off-line historical data, therefore, constantly changing conditions are not captured. Also, the data collected only provides information for a certain range of road segments due to constraints of current detectors. The same set of default parameters are used for simulating
different types of networks. Networks have distinguished properties and to simulate such networks, a simulation model needs to be calibrated accordingly. But, due to lack of sufficient data researchers have to use methods that are exhaustive and frequently results in inaccurate results and large discrepancies between observed and simulated data.

- **Statistical profiles based on spatial-temporal detailed data:**

  Currently, limited amount of data is available through inductive loop detectors. Mainly, it consists of counts and volume only. Other parameters such as delays, travel time, etc. are calculated using probability and regression techniques due to lack of sufficient data. Also, for such calculations, the data is assumed to be normally distributed which is rarely the case. Most of the statistical analysis studies focus on accident related effects on traffic, but the validation of such methods is hard due to lack of consistent and detailed data.

1.3 Proposed Method of Solution

The uniqueness of the research is the use of ‘mobile and elevated cameras’ that traverse the network providing complete wide-area monitoring data to the traffic management center in real-time, so that appropriate control decisions may be reached instantaneously, offering considerable improvements over existing methods of traffic data collection and road traffic monitoring. Statistical profiles are obtained and fed to traffic simulation models to get an accurate replica of the current state of the network as well as to predict future traffic patterns and take informed decisions in case of emergencies and future planning purposes.

The novel idea presented in this research effort is focusing on the fact that collected real-time video data may be incorporated into traffic simulation and real-time traffic control. In principle, video data may be used to evaluate traffic patterns over chosen areas, study possible network enhancements, update and calibrate traffic simulation models such that real-time changes in an
urban traffic system will be captured and discrepancies between actual and simulated traffic conditions will be minimized.

The way to implement this idea is by converting collected video data into ‘useful traffic measures’ that can be combined to obtain essential statistical profiles for traffic patterns. In essence, following the proposed approach, traffic parameters such as mean-speed, density, volume, turning ratio, origin-destination matrix, to name a few, may be derived accurately and be used to improve prediction of traffic behavior in real-time. Emergency response strategies and control of traffic using adaptive intersection signal control, ramp metering or variable message signs can also be planned and optimized in real-time. Derived parameters being the actual and dynamically updated ones may serve as inputs to commercial traffic simulation models.

It is important to emphasize that traffic simulation models play an important role in managing and evaluating traffic networks. Traffic engineers rely on accurate prediction of future traffic trends based on outputs from such models. Hence, calibration and update of these models becomes a very important and critical concern. Since current sensors such as inductive loops are unable to provide detailed data for such models, and since data collection following conventional techniques is a highly exhaustive and intensive procedure, mostly historical out-of-date data is used for calibration of these models. Therefore, the proposed alternative method is justified.

1.4 Research Contributions

This thesis provides a framework for integration of real-time unmanned helicopter-based video data into simulation models for improved traffic analysis. The following are some of the major contribution that this thesis provides:

- The “eye-in-the-sky” approach is utilized to obtain real-time traffic video data. This method of obtaining spatial-temporal video data overcomes the constraints and
limitations of existing traffic detectors that are expensive and only provide point-based data.

• Valuable insights about traffic behavior are gained by obtaining individual vehicle trajectories. Virtual detectors and virtual detection frames are utilized to directly obtain traffic measures such as speed, flow, occupancy and density. These parameters are further used in building significant traffic profiles. These statistical profiles check the quality of the data, accommodate errors and outlier observation values, and build a model to forecast short-time predictions based on current traffic trends.

• Traffic simulation models are developed based on statistical profiles. Network geometry and signal timings are incorporated into the model before including the traffic parameters obtained through statistical profiles. Measures of effectiveness / performance measures are obtained as results from the simulation model which may be utilized by traffic planners to choose between different scenarios or plans.

1.5 Summary of Results

Several case studies were conducted and data was obtained from multiple locations/intersections during the study. The video data was extracted into traffic counts and relevant properties of the traffic behavior were studied. Before using the data, several smoothing methods were implemented to clean and organize the data. Statistical analysis was performed on obtained data to obtain useful information and trends regarding the traffic behavior. Traffic simulation models such as Synchro and CORSIM were used to replicate the network geometry. The resulting parameters from the statistical analysis were input into simulation models to calibrate the network model with real-time properties and analyze traffic patterns. This approach proves to be beneficial in extracting information from real-time traffic data for immediate use.
1.6 Thesis Outline

The remaining thesis outline is as follows. Chapter 2 provides the background information for detection methods, unmanned vehicles, and simulation models. Chapter 3 covers the literature review on current methodologies in the field of data collection and analysis. Chapter 4 defines the formal problem statement in details. Chapter 5 describes the proposed solution adapted for this research. Chapter 6 covers the case studies conducted during the research along with the results. Finally, Chapter 7 presents the conclusion and suggests future work required in this field of study.
Chapter 2

Background Information

The necessary background knowledge for this research is provided in this Chapter. Section 2.1 describes the current surveillance methods, while the different types of simulation models are presented in Section 2.2. Section 2.3 gives an introduction to unmanned aerial vehicles and its usage in the industry.

2.1 Current Surveillance Methods

Traffic engineers require data of road usage to properly control existing traffic as well as planning for future increase in demand. Collecting field data is a very important aspect in traffic planning, as it is necessary to build a library of historical data of traffic on a network, to analyze and evaluate the traffic behaviors on a network. In order to obtain such data, several detectors are placed on the network. Vehicle detectors are used to generate information specifying the presence of a vehicle at a particular location. Traffic data collection is performed using inductive loops, sonar and microwave detectors, or vision sensors. Detectors are either embedded in the sideways or they are mounted over poles across the network.

Current methods such as detectors embedded in pavements or pneumatic tubes, and cameras mounted on towers have proven to be expensive and time-consuming. Moreover, these methods require lane closure and disruption to traffic during installation and periodic maintenance. The disadvantage of using such detectors is that they only provide local information as they are
installed on a fixed location, thus providing only point-based data since only a certain point or region of the network is targeted. Furthermore, the installation of such detectors is expensive and thus they cannot be used to cover large segment of a network. Except for vision sensors, other detectors are not proficient in detecting stationary or slow moving vehicles. Detectors do not provide sufficient detailed information about traffic data to accurately predict and estimate traffic flows due of their restriction of being stationary. It is not possible to move detectors once they are installed, further, they cannot provide useful information such as vehicle trajectories, routing information, and paths through the network. Also, only certain traffic parameters like vehicle presence, speed, count and occupancy can be calculated using loop detectors.

2.2 Why Unmanned Aerial Vehicles (UAVs)?

An alternate source of data collection is by using aerial vehicles that can hover around the network and collect much detailed traffic information. Aerial view provides better perspective with the ability to cover a large area and focus resources on the current problems. UAVs provide a better “bird’s eye view” which is capable of obtaining spatial-temporal data helpful in network surveillance. It has the advantage of being both mobile, and able to be present in both time and space. The advantage of UAVs is that they can move at higher speeds than ground vehicles, as they are not restricted to traveling on the road network. This can be very beneficial in emergency response scenarios as it permits timely view of disaster area to access severity of damage. Some private companies have been flying manned aircrafts for commercial usage and survey. But this approach does not prove to be cost-effective. Also, the manned aircraft cannot be flown in bad weather, or regions that are potentially unsafe for the operators. UAVs may potentially fly in conditions that are too dangerous for a manned aircraft, such as evacuation conditions, or very bad weather conditions.
UAVs may be semi- or fully- autonomous aircrafts that can carry cameras, sensors, communication equipment or other payloads. UAVs have been used for military applications since 1950s. Lately, increasing interest has been found in diverse civilian, federal and commercial applications, such as traffic monitoring. Figure 2.1 shows some different type of UAVs used by various universities and companies for aerial surveillance.

Figure 2.1. Several types of unmanned vehicles. Aerosonde UAV; MARVIN Autonomous Helicopter; Scandicraft Apid Mk III UAV; Karma Blimp.

UAVs are equipped with a variety of multiple and interchangeable imaging devices including day and night real-time video cameras to capture real-time video; sensors such as digital video,
infrared cameras, multi-spectral and hyper-spectral sensors, thermal, synthetic aperture radar, moving target indicator radar, laser scanners, chemical, biological and radiological sensors, and road weather information systems (RWIS) to record necessary information, such as weather, fire and flood information; and communications hardware to relay data to the ground station. With advances in digital sensing platforms, image processing, and computational speed, there are significant opportunities to automate traffic data collection. Different UAVs have different data collection capabilities. Some of them have real-time data transfer capabilities to the ground station, while the others are capable of storing high quality video or images on-board.

UAVs are classified as either rotary-wing or fixed-wing. Fixed-wing vehicles are simple to control, have better endurance, and are well suited for wide-area surveillance and tracking applications. Fixed wing vehicles have another advantage that they can sense image at long distances. One disadvantage though is that it takes sufficient time to react as turning a fixed-wing vehicle takes time and space until the vehicle regains its course. The rotary-wing vehicles are also known as Vertical Takeoff and Landing (VTOL) vehicles. They have the advantage of minimum launching time, as well as they do not need enough space for landing. They have high maneuverability and hovering. Rotary wing vehicles have short range radars and cameras to detect traffic movement. The drawback of such type of vehicles is that the rotary motion leads to vibration.

For detailed information about UAVs, a detailed report was prepared, which can be accessed online [1].

2.3 Hardware and On-board/Off-line Processing

Figure 2.2 shows the custom-made unmanned helicopter at the Unmanned Systems Lab. Each helicopter is equipped with custom made vision systems for on-board and on-the-ground data
processing, pan-tilt cameras for dynamic tracking and car-following, other sensors and mission specific controllers for robust hovering over intersections and assigned target areas.

Figure 2.2. Custom-made unmanned helicopter with on-board vision system and controllers.

Based on purpose of the traffic planning team, helicopters can fly to and hover over chosen intersections for simultaneous video data collection, and collect video data over surface street segments, traffic corridors, or highway segments. The preliminary work has been done keeping the UAV in a hovering state, that is, the source (camera) is fixed at a point, and can only observe a limited amount of network area. The area that can be covered by a particular camera is called the field of view (FOV) [2]. Thus, the observable distance can be denoted by d (FOV).

Figure 2.3. (a) shows a fixed camera pointing straight down (b) shows a camera tilted at some angle. The observable area is the camera’s field of view (FOV).
In figure 2.3(a), the camera on the UAV points straight down. In this case, the area \( A \) that can be observed is given by

\[
A = 2 \times (\text{Altitude}) \times \tan\left(\frac{\text{FOV}}{2}\right)
\]  

(2.1)

The camera that we have been working with in our lab (Sony block FCB-EX980S) has a horizontal Field of View of 42.2°. Given also that the maximum allowable altitude is currently 200ft (approx. 66m), the maximum area that can be observed is 50.9 m. In figure 2.3(b), the observable area is related to the Field of View (FOV) and the tilt angle \( \theta \) by the equation:

\[
A = \text{Altitude} \times (\tan(\text{FOV} + \theta) - \tan\theta)
\]  

(2.2)

This yields a value of observable area to be 165 m. This value doesn’t take into consideration the constraints posed by the requirement to accurately detect vehicles. The camera should not just be able to show the road but also to discriminate between vehicles. If that is taken into account the detection range is approximately 44 m. However, to calculate this value we assumed the only a portion of the whole image would be used for vehicle detection. Alternatively if the whole image is used for processing then the camera could be able to monitor a sizable part of a road (500m or more). If greater range for observation or for processing is required then a higher resolution camera should be used.

2.4 Image Processing

Each helicopter is equipped with a fully functional vision system with on-board and on-the-ground processing capabilities for image stabilization, object extraction, localization, motion
estimation, grouping, network geometry extraction, vehicle tracking and traffic patterns, on top of and in addition to a robust helicopter control system. Image processing for traffic applications involve primarily two tasks: identifying the environment (network geometry, lanes, etc.), and vehicle detection. Real-time outdoor image processing is a challenging task, as the system needs to adapt to changing light levels, shadows, environmental conditions, and variability in road and vehicle characteristics. Also, the system needs to have fast processing time, and high reliability. The source of video can be either through a static camera placed on a pole across an intersection/lane, or a moving camera mounted on a mobile vehicle, ground or aerial. An extensive survey of video processing techniques for traffic applications can be found in [3].

The on-board vision system has been designed to perform the following:

• Extract useful information about traffic in the form of statistical measures,
• Operate in rural, semi-rural or urban areas regardless of network geometries, and,
• Operate in real-time.

Figure 2.4 shows the different modules involved in the image processing process. The stabilization module overcomes vibrations inherent in a VTOL vehicle. The motion extraction module gathers information from the Inertial Measurement Unit (IMU) to extract the moving objects from the images, the configuration of which is relative to the camera. The feature extraction module is used to select features from the image sequence that most likely provide as much information as possible, such as edges and lines that can be matched to automobiles or to the silhouette of the road. The feature grouping module groups the features generated by the feature extraction module to allow for scene interpretation.

To fully exploit the capabilities of a mobile platform, the vision system is designed to adapt to different environmental setups. This environmental setup selection module contains algorithms to achieve this automatically. The structures containing the grouped features are tracked in the vehicle tracking module through the image sequence to estimate the trajectory each vehicle followed. Finally, the traffic statistics module receives all the information created in the system
and converts it to statistical measures. This module is able to count the total number of vehicles or turning vehicles at intersections based on the estimated vehicle trajectories and the extracted local network geometry.

Figure 2.4. Block diagram of the various image processing modules.

Accuracy, correctness and reliability of the obtained statistical profiles depend on vision system functionality. Therefore, the approach to be followed to collect and process visual data is presented first, followed by preliminary results on how the conversion will be accomplished. Several modules are required for efficient functionality of the vision system that will incorporate image stabilization (since both camera and the helicopter are moving), motion and feature extraction, environment setup, and vehicle tracking.

- Stabilization: Vehicle vibration introduces artifacts in the image sequence making objects in the image difficult to extract, localize and estimate their motion. To overcome this problem, the average of the last $N$ frames ($I_{\delta}$) is used rather than the last frame $I(t=N)$ itself. The ‘frame’ sent for further processing at any given time $t$ is given by:
\[ I_\delta(t) = \frac{1}{N} \sum_{k=0}^{N} I(t-k) \]  

- Motion extraction: The camera is not static; hence the apparent motion of any object or area within the image may be due to the ego-motion of the camera rather than the actual motion of the depicted object. In order to extract the moving objects from the images, the position and the attitude of the camera must be either known or be (somehow) estimated. This is accomplished using information provided by the vehicle IMU. Data acquired from the IMU is used to calculate the Focus of Expansion (FOE) coordinates on the image. The FOE is the point where all motion vectors corresponding to stationary points intersect. If the motion vector of an object does not point towards the FOE, it corresponds to a moving object.

- Feature extraction: The objective of this model is to select features from the image sequence that most likely provide as much information as possible. Given the application domain, characteristic features are: edges and lines that can be matched to automobiles or to the silhouette of the road; corners that are most likely to belong to automobiles; color that could identify the tarmac in contrast with the surroundings. One of the most effective edge detectors is the Canny filter. As alternatives to this computationally intensive filter a series of linear spatial filters like the Sobel or the Prewitt operators can be used to extract edges. Corners are extracted using the Harris operator or its modified version the Kanade-Lucas-Tomasi (KLT). Color can be represented in a variety of color spaces such as the Hue, Saturation, and Intensity (HSI), and the Lab which offer a representation closer to human color perception or the RGB, YUV that are closer to the image data format as they are provided by the sensor thus avoiding computationally intensive conversions.
Feature grouping: Features generated by the previous module are grouped to allow for scene interpretation. This function is performed by the feature grouping module. It accepts as input uncorrelated features, the outputs of the feature extraction module as well as information about their motion, and returns structures containing properties of the image objects. These properties include the object type (vehicle or environment) and motion vector. Features can either be grouped on the basis of the proximity and similarity to each other using a nearest neighbor approach, or be matched to a model representing the object. The first approach is quite straightforward in the sense that only the feature space needs be defined. The model approach requires a 2D or 3D model creation. In the latter case either the 3D model must be projected onto the 2D image and matched to the 2D features or the 3D world must be reconstructed by the extracted 2D features and then matched to the 3D model. Matching in 3D is more intensive computationally and should not be the first choice for a system with real-time performance requirements. However the use of 3D models or 2D templates is essential to expand the operation of the vision system to include vehicle type recognition.

Environment Setup Selection / Network Geometry Extraction: To fully exploit the capabilities of an airborne vehicle, the vision system must be able to adapt to different environment setups. This includes the ability to identify roads in urban, rural areas and extract their structure. Structures containing the grouped features are tracked through the image sequence to estimate the trajectory each vehicle follows. Grouped features extracted from each frame are matched with similar groups of features in subsequent frames. The most probable similarity match are found and the disparity between the position of this template or group of features in the previous and the current frame are calculated. After extracting the positions that an object has gone through, a trajectory is constructed by means of linear interpolation. This module is able to identify boundaries of the pavement and whether the image contains an intersection or a straight stretch of a
freeway. It organizes previously extracted features that correspond to objects belonging to the static environment. Lines previously extracted and grouped are compared with templates of various road configurations (3-way, 4-way intersections etc.). Templates may consist of linear or higher order segments. This function distinguishes the proposed system from existing ones, since most of the applications so far rely on a given description of the road system or have assumed a static environment that allows the road structure to be easily and accurately superimposed on the image.

- Vehicle tracking: The structures containing the grouped features are tracked through the image sequence to estimate the trajectory each vehicle follows. The grouped features that are extracted from each frame are matched with similar groups of features in subsequent frames. The similarity measure is either a measure of distance between the two feature vectors in the feature space or a correlation based technique that compares the pixels in each region. In any case, the most probable match is found and the disparity between the position of this template or group of features in the previous and the current frame is calculated. After having extracted the positions that an object went through, a trajectory can be constructed by means of linear interpolation. Figure 2.5 shows the steps that take place to stabilize and extract vehicle information from a given video data feed from a helicopter.
Traffic simulation models are computer software packages that are used to track movement of vehicles through a network based on operational settings defined by the user. These packages have proved to be very useful to traffic engineers to check the performance of various control strategies before implementing them on the actual network. Also, most of these simulation models provide a visual interface, which is very beneficial to see the traffic pattern development. The steps involved with a traffic simulation model are setting up the network geometry along with the network parameters, loading the model with vehicles, tracking the movement of vehicles through the network, and obtaining the results to determine measures of effectiveness.

Several simulation models such as CORSIM, SYNCHRO, VISSIM and PARAMICS are commercially available and are used by the transportation industry to analyze traffic patterns and
evaluate alternate traffic control and behaviors. Traffic engineers rely on accurate predictions of future traffic trends based on outputs from such models. Hence, calibration and update of these models becomes a very important and critical concern to minimize the discrepancies between simulation output and actual traffic measures. Since current sensors are unable to provide detailed data for such models, and since data collection following conventional techniques is a highly exhaustive and intensive procedure, mostly historical out-of-data is used for calibration of these models. Moreover, since each traffic network component (segment) has distinct characteristics, one cannot use the same set of calibrated data set and parameter values in all network components to predict traffic. Each simulation model needs to be calibrated based on the specific network’s unique features and traffic patterns. Thus, mismatch and discrepancies between predicted traffic situations (output of simulation models) and actual traffic pattern occur.

Transportation simulation models require infrastructure data, including road network geometry, link speed limit and traffic signal timing plans, as well as traffic data, such as origin-destination (OD) demand, link travel speed and link flows. In traditional traffic models, the traffic data is incorporated as ‘static data’, meaning that demand and flow parameters are considered fixed throughout the simulation period. More recently, models have begun to treat these parameters as ‘dynamic’, thus, accounting for the variation of traffic conditions with time. The generated statistical profile can be periodically input into these simulation models to keep them up-to-date, improve accuracy, parameter calibration and reliability of traffic simulation models, thus, improve traffic prediction.

This Chapter described the background information related to current surveillance methods, unmanned aerial vehicles and their capabilities; hardware used for the research, image processing techniques, and traffic simulation models. The next Chapter provides with the literature review related to research conducted in field of transportation such as traffic surveillance methods, aerial surveillance, traffic simulation models and statistical methods involved in transportation research.
Chapter 3

Literature Review

This Chapter provides a comprehensive literature review conducted during this research. It covers sections such as current traffic surveillance / detection methods, aerial surveillance and UAVs, traffic simulation models and their characteristics, and statistical methods used in transportation research.

3.1 Detection Methods

The first vehicle detector was invented in 1928 and installed in Maryland [4]. This type of detector had a passive roadside transducer that registers a vehicle when the horn of the vehicle was activated. The pressure sensitive type detectors followed, which were embedded in the roadbed. Vehicles were detected by the vehicle weight when the vehicles passed over the detector. Traditional technology for traffic sensing, including inductive loop detectors and video cameras, are positioned at fixed locations in the transportation network. Data related to traffic flow is currently obtained from detectors embedded in pavements or pneumatic tubes stretched across roads. While these detectors do provide useful information and data about traffic flows at particular points, they generally do not provide useful data for traffic flows over space. Table 3.1 lists current sensor technologies and compares their strengths and weaknesses.
Table 3.1. Strengths and weaknesses of several detection technologies. [5]

<table>
<thead>
<tr>
<th>Technology</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inductive Loop</td>
<td>• Flexible design to satisfy large variety of applications</td>
<td>• Installation requires pavement cut</td>
</tr>
<tr>
<td></td>
<td>• Mature, well-understood technology</td>
<td>• Decreases pavement life</td>
</tr>
<tr>
<td></td>
<td>• Large expensive base</td>
<td>• Installation and maintenance require lane closure/disruption of traffic.</td>
</tr>
<tr>
<td></td>
<td>• Equipment cost is lower compared to non-intrusive detector technologies.</td>
<td>• Wire loops subject to stresses of traffic and temperature</td>
</tr>
<tr>
<td></td>
<td>• Provides basic traffic parameters (e.g. volume, presence, occupancy, speed, headway, gap)</td>
<td>• Multiple detectors usually required to monitor one intersection</td>
</tr>
<tr>
<td></td>
<td>• Operability in harsh environments.</td>
<td>• Accuracy may decrease when design requires detection of a large variety of vehicle classes</td>
</tr>
<tr>
<td>Microwave Radar</td>
<td>•Insensitive to inclement weather</td>
<td>• These sensors cannot detect stopped vehicles.</td>
</tr>
<tr>
<td></td>
<td>• Direct measurement of speed</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Multiple lane operation available</td>
<td></td>
</tr>
<tr>
<td>Active Infrared</td>
<td>• Transmits multiple beams for accurate measurement of vehicle position, speed, and class.</td>
<td>• Operation may be affected by fog when visibility is less than 20 feet or blowing snow is present.</td>
</tr>
<tr>
<td></td>
<td>• Multiple lane operation available</td>
<td>• Installation and maintenance, including periodic lens cleaning, require lane closure.</td>
</tr>
<tr>
<td>Ultrasonic</td>
<td>• Capability of over height vehicle detection</td>
<td>• Environmental conditions such as temperature change and extreme air turbulence can affect performance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Large pulse repetition periods may degrade occupancy measurement on freeways with vehicles traveling at moderate to high speeds</td>
</tr>
<tr>
<td>Video Image Processor</td>
<td>• Monitors multiple lanes and multiple zones/lanes</td>
<td>• Inclement weather such as fog, rain and snow; vehicle shadows, occlusion etc. can affect performance</td>
</tr>
<tr>
<td></td>
<td>• Easy to add and modify detection zones</td>
<td>• Requires 50- to 60- ft camera mounting height for optimum presence detection and speed measurement</td>
</tr>
<tr>
<td></td>
<td>• Rich array of data available</td>
<td>• Susceptible to camera motion caused by strong winds</td>
</tr>
<tr>
<td></td>
<td>• Provides wide-area detection when information gathered at once camera location can be linked to another</td>
<td></td>
</tr>
</tbody>
</table>
Visual data obtained through video cameras provide detailed traffic information such as delays, vehicle classification, traffic density, and turning movements [6]. Stationary video cameras are installed at locations to capture detailed information about traffic such as vehicle trajectories, which may not be obtained using detectors. Most of these cameras mimic the operation of loop detectors. These cameras are calibrated to focus on a particular region of the road and only detect the vehicles that pass through this region. Several commercial systems such as AUTOSCOPE, IMPACTS and CCATS [7] detect presence of vehicles using image intensity changes in the pre-specified region. Coifman et al. [8] provides details about other “third generation” systems which are capable of tracking vehicles but have problems with occlusion, camera vibrations and lighting transitions. California Partners for Advanced Transit and Highways (PATH) installed a surveillance system called Berkeley Highway Laboratory (BHL), which is a combination of detector stations along a freeway and video cameras on top of a 30-story building across the I-80 freeway [9]. This system is connected through coaxial cables to a server where the data is stored, followed by off-line data processing. This system of capable of detecting vehicles and generating vehicle trajectories based on obtained data [10].

The Virginia Department of Transportation (VDOT) installed video based traffic detectors along Route 7 [11]. The cameras were mounted on the mast arms at the far side location of the signal post with a seven-foot riser. Once the detector positions are established, the camera cannot be moved, or else the complete system needs to be reconfigured. The system was discontinued because of significant detection errors such as over counting traffic volumes, unable to accurately register left turn demand, and occlusion issues.

Different approaches of using moving cameras in traffic surveillance are possible. Some studies employ floating cars to investigate travel time and other traffic conditions [12]. For example, McDonald et al. [13] used two cameras that were mounted on either side of a bus roof, while the bus moves in the center lane at a constant speed. The cameras gather data of vehicles moving in adjacent lanes and send it to the base control station. Video data was used to obtain
information on lane usage, lane changing rates, vehicle headways, and average speeds. However, using cameras mounted on a bus roof does not solve the problem of wide area surveillance, as the altitude of the positioned cameras does not allow for a good view of the vehicles and the network.

Several on-going research projects have been working to come up with technologies that improve surveillance techniques for traffic management. Image processing techniques have also been used for lane detection and vehicle detection [14, 15]. Systems such as SCARF and UTA [16] use moving cameras and image processing techniques for lane detection, edge detection, and image segmentation. A research conducted by PATH [17] designed a system $V^2$SAT that tracks vehicles using vehicle signature analysis. Video cameras were placed on an over-crossing that tracked each vehicle passing through a pre-calibrated region. The detection region was limited to one lane, and travel-time was manually observed. Travel time estimation algorithms such as Extrapolation method and Platoon matching have been developed based upon measurable point parameters such as volume, lane occupancy etc. Image matching algorithms are used to match vehicle images or signatures captured at two consecutive observation points.

3.2 Aerial Surveillance and UAVs

Satellites were initially considered for traffic surveillance purposes, but the transitory nature of satellite orbits make it difficult to obtain the right imagery to address continuous problems such as traffic tracking [8]. Also, cloud cover hampers good image quality on days with bad weather. Manned aircrafts are deemed expensive for traffic surveillance studies and are non-operational in severe weathers as well as potentially unsafe environments due to presence and safety concern of operators. UAVs, on the other hand, can fly at low altitudes and do not involve risk of operators. They may be employed for a wide range of transportation operations and planning applications such as incident response, monitor freeway conditions, traffic signal control coordination, traveler
information, emergency vehicle guidance, vehicle tracking on intersections, measurement of typical roadway usage, and estimation of Origin-Destination flows [19].

Several types of aerial surveys have been used or tested to measure data related to traffic management. The method of using fixed-wing aircraft to collection congestion and traffic information was being used as early as 1965 by a transportation consultant in Maryland. Researchers at the University of Karlsruhe in Germany examined the matching of vehicle images from aircraft in 1987. New methods of improving this technology are under development and research around the world. Researchers have tried experimenting on fixed-wing aircraft, helicopters, observation balloons and satellites.

Kumar et al. [20] describes the challenges faced during aerial video surveillance using manned helicopters and a video camera, such as limited field of view, data storage and subsequent analysis problems, and difficulties in interpreting the captured video. As such, the research team is developing VTOL vehicle technology to improve the flexibility of video traffic surveillance. Another research using manned helicopter used image registration and vehicle recognition to gather useful information such as travel time, density and queue estimation [21].

Several research teams in the U.S. and around the world have recognized the potential of unmanned aerial vehicles (UAV) for traffic monitoring. Most projects have focused on development of the UAV technology, such as navigation and communications systems; however, recently advances have also been made in image processing for mobile-source videos. Further, while researchers have begun to consider integration of the UAV and image processing systems into real-time traffic and emergency management systems, a complete and working system has not been developed. New methods of improving this technology are under development and research at various universities. Several ongoing transportation-related research efforts using UAVs are listed below.
• University of Florida research team is working with UAVs for aerial traffic surveillance on rural interstates. The airborne traffic surveillance system (ATSS) [22] proof-of-concept project [23] aims at evaluating the feasibility of the wireless communication systems, that the UAV can fly for a certain distance collecting traffic information and successfully transmit it to the base stations.

• The Wallenberg Laboratory for Information Technology and Autonomous Systems (WITAS) is conducting a long-term basic research project on UAVs at the Linkoping University (LiU), Sweden [24]. They are developing technologies and functionalities necessary for successful deployment of a fully autonomous UAV operating over diverse geographical terrain containing road and traffic networks. The UAV is intended to navigate autonomously at different altitudes, plan for mission goals such as locating, identifying, tracking and monitoring different vehicle types. The project also aims for identifying complex patterns of behavior such as vehicle overtaking, traversing of intersections, parking lot activities, etc.

• The research at Ohio State University (OSU) is pioneered by National Consortium on Remote Sensing in Transportation (NCRST). Field experiments were conducted on different freeway scenarios, collecting information on freeway conditions, intersection movements, network paths and parking lot monitoring [25]. Traffic parameters such as flows, speeds, densities, off-ramp weaving, vehicle trajectories, turning movements and queue lengths on intersections were observed while gathering information on a network consisting of seven intersections. The data obtained was used to derive parameters such as average annual traffic data, queue length, and local origin-destination flow estimation.

• Traffic Surveillance Drone [19] is being developed at the Georgia Tech Research Institute’s (GTRI) Advanced Vehicle Development and Integration Laboratory. Their initial effort involves the development and working of a prototype to demonstrate the capabilities of traffic data collection, and be able to relay live video and two-way audio
from the site of traffic incidents, back into the state’s Advanced Traffic Management System (ATMS).

- The European Commission’s COMETS project is focusing on “understanding” the traffic environment to serve as a mobile sensory platform with real-time information gathering and processing capabilities. They intend to monitor traffic conditions, identify and track individual vehicles, and gather data related to network use and abuse [26].

- University of Arizona supported by NCRST-F has gathered aerial video data to study the video image properties, and to characterize the quality of data for traffic measurements [27]. The project attempts to examine the integration of digital video, GPS, and automated image processing to improve the accuracy and cost-effectiveness of data collection and reduction.

- Western Michigan University has recently started work on Application of UAVs to Traffic and Emergency Surveillance. Focus is to see the applicability, and analyzing traffic using aerial images [28].

For completion, a comprehensive survey on types of UAVs and their capabilities can be found in [1].
### Table 3.2. List of current research work being undertaken at various universities.

<table>
<thead>
<tr>
<th>Research</th>
<th>Team</th>
<th>UAV</th>
<th>Objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ohio</td>
<td>Ohio State University</td>
<td>MLB BAT3</td>
<td>Application of UAV for surface transportation surveillance</td>
</tr>
<tr>
<td></td>
<td>Ohio DOT</td>
<td>(Fixed Wing)</td>
<td>Collecting information on freeway conditions, intersection movements, network paths, and parking lot monitoring.</td>
</tr>
<tr>
<td></td>
<td>NCRST</td>
<td></td>
<td>Traffic parameters measured</td>
</tr>
<tr>
<td>ATSS</td>
<td>University of Florida</td>
<td>Aerosonde</td>
<td>Use of UAV with video for data collection</td>
</tr>
<tr>
<td>(UFL)</td>
<td>Florida DOT</td>
<td>(Fixed Wing)</td>
<td>Define communication links using current FDOT microwave system</td>
</tr>
<tr>
<td></td>
<td>Tallahassee Commercial Airport</td>
<td></td>
<td>Timely information on transportation networks - both rural and urban</td>
</tr>
<tr>
<td></td>
<td>RWIS Research Team</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WITAS</td>
<td>Linkoping University, Sweden</td>
<td>Scandicraft Apid Mk 9</td>
<td>Develop technologies for deployment of fully autonomous UAV</td>
</tr>
<tr>
<td></td>
<td>(Rotary wing)</td>
<td></td>
<td>Integrate autonomy with active vision system</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Identifying complex patterns of behavior (vehicle overtaking etc)</td>
</tr>
<tr>
<td>COMETS</td>
<td>LAAS</td>
<td>MARVIN (Rotary)</td>
<td>Design and implement a distributed control system for</td>
</tr>
<tr>
<td></td>
<td>CNRS</td>
<td>Karma Biplar (Fixed)</td>
<td>Cooperative detection and monitoring using heterogeneous UAVs.</td>
</tr>
<tr>
<td></td>
<td>Real-time Systems &amp; Robotics</td>
<td>Remotely Piloted</td>
<td>Control architecture and technique of real-time control.</td>
</tr>
<tr>
<td></td>
<td>ADAP</td>
<td>helicopter (Rotary)</td>
<td>Integrating distributed sensing techniques with real-time imaging</td>
</tr>
<tr>
<td></td>
<td>CVL</td>
<td>HELIV</td>
<td></td>
</tr>
<tr>
<td>Arizona</td>
<td>University of Arizona</td>
<td>Manned</td>
<td>Use of Manned Helicopter</td>
</tr>
<tr>
<td></td>
<td>NCRST-F</td>
<td></td>
<td>Deriving vehicle trajectories from video</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Traffic parameters measured</td>
</tr>
<tr>
<td>Minnesota</td>
<td>University of Minnesota</td>
<td>Unknown</td>
<td>Autonomous traffic monitoring</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Determining traffic parameters</td>
</tr>
<tr>
<td>Traffic Surveillance Drone</td>
<td>Georgia Tech Research Institute</td>
<td>Customized Drone</td>
<td>Development of generic VTOL advanced controllers.</td>
</tr>
<tr>
<td></td>
<td>Georgia DOT</td>
<td>(Rotary wing)</td>
<td>Fault-tolerant and Autonomous operation algorithms.</td>
</tr>
<tr>
<td></td>
<td>Federal Highway Administration's</td>
<td></td>
<td>Achieve dynamic performance and flight control command generation.</td>
</tr>
<tr>
<td></td>
<td>Priority Technology Program</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ultimate</td>
<td>University of California, Berkeley</td>
<td></td>
<td>Intelligent guidance systems for UAV</td>
</tr>
<tr>
<td>Auto-Pilot</td>
<td>Office of Naval Research's</td>
<td>(Fixed Wing)</td>
<td>Strategies of path-planning</td>
</tr>
<tr>
<td></td>
<td>AINS Program</td>
<td></td>
<td>Augment GPS with machine vision</td>
</tr>
<tr>
<td>Bridgewater State</td>
<td>USDOT's RSPA</td>
<td>MLB BAT3</td>
<td>Autonomous UAV to collect and interpret real-time traffic data</td>
</tr>
<tr>
<td></td>
<td>NASA</td>
<td>(Fixed Wing)</td>
<td>Gather multi-modal data using road-following capabilities</td>
</tr>
<tr>
<td></td>
<td>Bridgewater State College</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>University of Massachusetts</td>
<td></td>
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<tr>
<td></td>
<td>MLB Company</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ETH Zurich</td>
<td>ETH</td>
<td>Customized UAV</td>
<td>Traffic Surveillance</td>
</tr>
<tr>
<td>ORCA</td>
<td>Carnegie Mellon University</td>
<td>Customized UAV</td>
<td>Develop a vision-based robot helicopter which can operate</td>
</tr>
<tr>
<td></td>
<td>(Rotary)</td>
<td></td>
<td>autonomously to carry out well-structured mission goals</td>
</tr>
</tbody>
</table>
3.3 Simulation Models

Classic traffic flow models are based on the perception and reaction of a driver on a short time-scale. According to the level of implementation detail, models may be classified as macroscopic, mesoscopic, and microscopic.

The macroscopic approach (fluid-dynamic theory) utilizes analogies from fluid dynamics, such that traffic is considered to comprise of a one-dimensional flow of compressible fluid (cars) [29]. Such models use fluid variables (flow and density) to describe congestion and they do not model individual vehicles. There is a continuous effort to find a density-flux relation to better understand the traffic flow phenomenon.

The microscopic approach describes vehicles and drivers, individually. Each vehicle is represented by a particle, and the interactions between these particles depict the behavior and response of one vehicle towards the others. Several traffic phenomena such as vehicle characteristics for acceleration and braking, driving behavior such as route choice, lane change, gap acceptance, overtaking, are integrated in such models. Such models offer a more realistic description of the traffic pattern through a network of roads [30]. Micro simulators have been proven useful to design intersections, regulate traffic lights, study impact of variable message signs, ramp metering, etc. Approaches such as cellular automata [31, 32, 33], and agent technology [34, 35] are used to build these micro simulation models.

The mesoscopic approach based model is between the macroscopic and microscopic level as it combines the theories of both. Models are based on aggregate variables that do not distinguish between individual vehicles. They may use speed-density laws instead of detailed descriptions of the motion of individual vehicles. The dynamics of these variables in space and time are derived from microscopic assumptions on driver behavior.

Optimal velocity models are based on the assumption that the desired speed of a vehicle depends on the distance-headway of the leading vehicle. The vehicle maintains a safe speed
depending on relative position, rather than relative speed of the leading vehicle. It may be observed that the vehicle will stop if a minimum safe distance is reached. Similarly, the vehicle may obtain a maximum speed if the distance increases significantly.

Models may be also categorized as ‘time-based’ or ‘event-based’. In time-based models, simulation follows a pre-defined time step. At each time step, individual vehicles and their behaviors are computed and observed. A time-step is divided into two phases: a motion phase computing vehicle variables for all vehicles, and a decision phase where drivers may alter their vehicle behavior according to traffic conditions. Event-based models require less computation as updating vehicle variables occur only when an event occurs. This is because system variables are only affected when an event occurs. An event may be a vehicle entering or leaving a network, vehicle changing lanes, driver changing routes, etc. The problem with event-based models is that a single decision of a driver may impact several vehicles, which can sometimes lead to high computational complexity.

This research focuses on microscopic models based on car-following theories according to principles of classical Newtonian dynamics giving a deterministic description of the motion of individual vehicles. Each individual ‘particle’ in a system of interacting classical particles is represented by an individual vehicle in the traffic system that behaves as a stimulus-response system. Vehicle acceleration or deceleration is regarded as response of the particle to stimulus in the form of interaction with other vehicles in the system. From models that use car-following theory, earlier models [36] include follow-the-leader (driving strategy) and optimal velocity models. The stimulus in such models is the difference between two consecutive \((n\text{ and } n+1)\) vehicles. It has been suggested in [37] that each driver must maintain a safe distance from the leading vehicle by keeping the same speed with that of the leading vehicle. Time lag is introduced as the time taken by the driver to respond to the stimulus.
AIMSUM2 (Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks) has been developed at the Polytechnic University of Catalonia, Barcelona [38]. It supports the car-following theory and it is capable of simulating real traffic conditions in an urban network. It can evaluate different traffic control systems (fixed, variable, and adaptive) and different management strategies (route guidance, VMS). It is also capable of generating and model incidents, conflicting maneuvers, etc. The MOEs provided by AIMSUN2 are traffic flows, travel times, speed, etc. Different types of vehicles and drivers can be defined [39].

AIMSUM2 requires network description, traffic signal control plans, and traffic conditions as input parameters. These include traffic flows for input links, turning proportions at junctions, and the initial state of the network [38]. AIMSUN2 is integrated into the GETRAM (Generic Environment for Traffic Analysis and Modeling) that consists of a traffic network graphical editor, a network database, static assignment models, temporal simulation models and a module for storing and presenting results. Also, AIMSUN2 can be integrated with SCOOT (Split Cycle Offset Optimization Technique) to design signal timings for minimizing traffic delays [40].

CORSIM (CORridor microscopic SIMulation) developed by FHWA, integrates two existing software models: NETSIM (urban) and FRESIM (freeway). CORSIM is a core component in the TSIS (Traffic Software Integrated System), an integrated development environment that enables users to conduct traffic operations analysis. It is capable of simulating traffic flow in large urban areas containing surface streets and freeways [41].

CORSIM encourages the concept of network partitioning by dividing the network into many sub-networks connected to each other using interface nodes. It is capable of modeling pre-timed and actuated signal controls. Drivers are distributed based on their level of aggressiveness. Other distributions based on driver behavior are discharge headway, amber interval response time, and turning movements.

The input part of CORSIM is done through ASCII files, or the user can create graphically the whole network. Due to the large number of parameters considered by CORSIM, the input process
is confusing and time consuming. The output produces MOEs such as queue delays, time traveled, average speed.

INTEGRATION was developed at Queens University. It is now a privately owned model maintained by researchers at Virginia Tech [42]. It is a meso-scopic model that supports route-based guidance and traffic assignment routines on both street networks and integrated freeways. It uses combined theories of individual vehicles and macroscopic flow theory in the model. Parameters such as traffic control, route guidance and assignment may be used to vary the traffic pattern. The limitation though is that driver behavior cannot be changed by the user. One of the main capabilities of INTEGRATION is the assessment of real-time route guidance. MOEs are in form of travel time, distance, number of stops, queue sizes [43].

PARAMICS (PARallel MICroscopic Simulation) is a suite of high performance software tools for microscopic traffic simulation developed by the Edinburgh Parallel Computing Center and Quadstone Ltd., UK. This model has a comprehensive visual display supporting 3-D vehicle animation. PARAMICS can currently simulate the traffic impact of signals, ramp meters, loop detectors linked to variable speed signs, VMS and CMS signing strategies, in-vehicle network state display devices, and in-vehicle messages advising of network problems and re-routing suggestions [38]. It has a user friendly GUI for building network. It can load network data from standard node and link data sets such as SATURN, NESA or TRIPS. A notable feature of Paramics is its scalability. A large network can be decomposed into regions where each is simulated on a processor in a parallel machine. Output consists of traffic flow, density, signal phases, vehicle routing, real-time statistical output etc. [41].

SYNCHRO and SIMTRAFFIC are part of a simulation software package developed by Traffieware Ltd. Synchro is a macroscopic model, used in modeling traffic flow and optimizing traffic signal timing. Synchro takes a single file with data about multiple signalized intersections, and is used to optimize signals, and minimize delays and queues. SimTraffic is the visualization tool for Synchro that fully simulates signals, links and unsignalized intersections [44].
VISSIM (Verkehr In Staedten SIMulation), a German acronym for traffic in towns – simulation, is a discrete, stochastic, and time step based microscopic simulation model developed at the University of Karlsruhe, Germany. The model consists of a traffic simulator and a signal state generator. VISSIM is used for optimal vehicle actuated signal control strategies, testing various layouts of complex intersections etc. VISSIM can import the signal timing plans of three TEAPAC programs: PRETRANSYT, TRANSYT-7F, and SIGNAL97. The inputs include lane assignments and geometry, OD matrices or flow rates, turning percentages, distribution of vehicle speed, acceleration, deceleration, gaps, and signal control timing plans. VISSIM successfully outputs MOEs such as total delay, stopped-time delay, stops, queue lengths, etc. [41].

Another category of traffic models is dynamic traffic assignment models. Dynamic traffic assignment models estimate user optimal travel paths and equilibrium network conditions by iterating between traffic simulation and assignment of vehicles to paths. Unlike simple traffic simulation, traffic assignment models capture travel route choice behavior. In this case, rather than calibrating link counts, the origin-destination trip table is adjusted until the equilibrium assignment yields link flows that reflect observed values (such as those reported by video data).

Several dynamic traffic assignment models have also been proposed, including DYNASMART, DYNAMIT, INTEGRATION, VISTA, and TRANSIMS model. Dynamic traffic modules utilize simulation models combined with real-time traffic information to predict effects of various traffic management strategies. Data such as link speeds, link flows and route choice are collected from several sources of real-time information like loop detectors, roadside sensors, and GPS-equipped vehicle probes [45].

DYNASMART-X is a model being developed at the University of Maryland for traffic estimation and prediction, which interacts continuously with multiple sources of real-time information [46]. A very detailed review of dynamic traffic assignment (DTA) models can be found in [47].
DynaMIT is another real-time model developed at the Intelligent Transportation Systems Program at MIT. DynaMIT uses historical, surveillance and O-D data to generate reliable O-D estimates in real-time [48]. DynaMIT uses historical data with real-time inputs from field installations, surveillance data and control logic of traffic signals, ramp meters, and toll booths, to generate estimate future traffic conditions. MIT is assisting University of Virginia in performing calibration and identification of key parameters for a test network to integrate real-time traffic data into DynaMIT.

The Next Generation Simulation (NGSIM) program at Berkeley is developing behavioral algorithms for microscopic traffic simulation, supported by validated data sets. These data sets are provided by Berkeley Highway Lab (BHL) video surveillance system that consists of video cameras placed on roof of a building. Data is collected for a subsection of freeway I-80 on both directions. Data set consists of detailed vehicle trajectory data obtained by video cameras, wide area loop detectors, and other sources for signal/intersection data [49]. A detailed analysis of the dataset was conducted to calculate parameters such as flow, speed of vehicles, number of lane changes, headway and gap analysis, etc. The dataset has been made available online for use in researchers and simulation model developers at the NGSIM website [50].

Wahle et al. [51] has modeled the impact of real-time information on traffic patterns using an agent-based model. Data for these dynamic agents are collected by floating cars employed to investigate traffic conditions on routes. The impact of the driver as an agent and its behavior on traffic patterns was studied and discussed. Mazur et al. [52] have established an advanced traffic information system, OLSIM, which is an internet based cellular automata simulator. The simulator uses locally measured traffic data, provided every minute by about 4000 loop detectors and infrared or radar detection devices. This data is stored in a database at the central OLSIM server, and also includes control states of about 1800 VMS. The internet user can get the information about current traffic state, as well as 30 minute and 1 hour prognosis for the autobahn network in North Rhine-Westphalia.
A study conducted by Wayne State University, Detroit, MI, describes a real-time traffic simulation system used as a computational component in a real-time traffic system. The goal was that the system would be fed with real-time traffic input data, and it would predict traffic conditions in real time [53]. Tests with real data from the I-94 freeway in Minneapolis were conducted on a parallel macroscopic model. The idea was to validate the accuracy and computational rate of the system. In another work, Zou et al. [54] have developed a simulator model to integrate knowledge base and simulation system for real-time incident management. An input interface module suggests the location of the incidence, while the simulation module along with the knowledge-base/prediction module is used to primarily estimate the effects of the incident. An output module then monitors and assesses the varying traffic conditions after the incident.

3.4 Statistical Modeling of Traffic Parameters

Transportation related problems are stochastic in nature due to the presence of people with different driving behavior. This leads to high degrees of uncertainties while conducting transportation studies. Moreover, the complexity of transportation problems along with the high number of parameters affecting traffic requires certain set of statistical analysis methods to estimate system performance. In traffic studies, researchers are required to use certain tools or formulations to establish traffic patterns and response to events. While evaluating existing traffic simulation models that use different measure of effectiveness (MOE), ‘sensitivity analysis’ [55] reveals that there exist a few input parameters that actually affect the output and MOEs. Since current sensors are unable to provide detailed data for such models, and since data collection following conventional techniques is a highly exhaustive and intensive procedure, simulation models are validated using statistical analysis on such parameters. Due to lack of data, these input parameters are measured using statistical methods including sensitivity analysis [55, 56],
analysis of variance [57], chi-square tests [58], regression analysis [59], Wilcoxon signed-rank test [60], Theil’s inequality coefficient [61], spectral analysis [62], and the standardized time series technique [63].

The range of statistical models commonly applied in transportation studies includes binomial, Poisson, Poisson-gamma (or negative binomial), zero-inflated Poisson and negative binomial models, and multinomial probability models [64]. Johansson [65] uses Poisson and negative binomial count data models to estimate the effect of lower speed limits on number of accidents leading to damage Swedish motorways. Okutani et al. [66] describes a kalman filtering approach to predict short-term traffic volume. Other methods used to predict short term traffic flow include k-nearest neighbor approaches [67], exponential filtering [68] and ARMA models [69]. Regression techniques such as multiple linear regression are used to determine traffic safety variables [70]. Other methods such as genetic algorithms [71] and Bayesian analysis [72] are used to calibrate performance measures for simulation models.

Most existing methods used to measure traffic variation are focused on freeways. Rakha et al. [73] investigates traffic variability on freeways using ANOVA, least square error, and least Poisson error. Wang et al. [74] used an extended kalman filter for traffic state estimation for real-time freeway scenario. Data is collected using a series of traffic detectors located on a freeway stretch. Important parameters such as flow, density, capacity and speed were observed and analyzed for traffic state estimation. Stathopoulos et al. [75] examined the spatio-temporal variations of traffic flow in an urban network by using exploratory analysis of characteristics of several traffic parameters obtained over a period of several months. Tsekeris et al. [76] used principal component analysis as an approach for spatio-temporal analysis of variation of traffic flow.

Several classic hypothesis tests are used to validate simulation models. These tests include Kolmogorov-Smirnov test, Mann-Whitney test, two-sample t-test etc. These tests assume that the data is independent and have a normal distributed. But in common practice, mostly the traffic data
is non-stationary and autocorrelated. Thus, the above mentioned tests cannot be used for validity of the simulation model. Also, some approaches assume that traffic flow follows a normal distribution [77], which is seldom the case.

This Chapter provided the literature review of various researches conducted in field of transportation. The next Chapter defines the problem statement and definition of this research, and mentions the novelties of this research work.
Chapter 4

Problem Statement and Definition

Traffic conditions over the affected network may change significantly with time. Time-varying parameters such as queue length, average delay and speed are difficult to project using existing simulation models. Real-time data is required to give a reliable estimate of traffic conditions in such scenario. The discussion of problems faced with current approach and the subsequent novel approach presented in this work is as follows.

- Real-time data collection:

  The current approach is described as follows. Data is collected using stationary devices such as loop detectors embedded in pavements or video cameras mounted on poles. This data lacks the advantage of spatiality because it only covers a certain segment of the network. Current data collection methods rely on storing data on-site. Data is later retrieved for off-line processing.

  The novelty of this approach is described as follows. Data is collected in real-time using a video camera mounted on UAV. Video data provides a level of detail unavailable from other types of sensors that tend to provide only count-based information. Helicopters can traverse the network providing complete wide-area monitoring data to the traffic management center in real-time. This data contains detailed spatial-temporal information of the current traffic behavior. Data can either be processed on-site and relayed to the base station, or the raw video feed is transferred through wireless channels to the base station for off-line processing. Both processes occur in real-time, thus enabling the data analysis and statistical profiling immediately.
• Statistical profiles based on spatial-temporal detailed data:

The current approach is described as follows. Limited amount of data is available through inductive loop detectors. Mainly, it consists of counts and volume. Other parameters such as delays, travel time, etc. are calculated using probability and regression techniques due to lack of sufficient data. Most of the statistical analysis studies focus on accident related effects on traffic, but the validation of such methods is hard due to lack of consistent and detailed data.

The novelty of this approach is described as follows. Detailed spatial-temporal data is observed and collected using UAVs. Vehicle trajectories are obtained which give useful information about volume, vehicle spacing, density, travel time, delay, turning movement, queue length and O-D estimates. These are useful to obtain the traffic pattern on a particular segment. Moreover, video data allow for differentiation of vehicle types resulting in more detailed traffic analysis and control. With such detailed profiles, it will be feasible to observe key simulation parameters and observe how they affect measure of effectiveness.

• Calibration and update of simulation models in real time:

The current approach is described as follows. A simulation model is calibrated using limited amount of data. Although current simulation models have the ability to model complex traffic behaviors, models are typically calibrated based on off-line historical data, therefore, constantly changing conditions are not captured. Most traffic simulation studies have used data collected through fixed detectors or stationary cameras mounted on poles along the road. The disadvantage of this data is that it only provides information for a certain range of road segments. The same set of default parameters are used for simulating different types of networks. Many researchers have suggested that networks have distinguished properties and to simulate such networks, a simulation model needs to be calibrated accordingly. But, due to lack of sufficient data researchers have to use methods such as trial-and-error, Bayesian, neural network etc. to update the simulation model. This process is exhaustive and frequently results in inaccurate results and large discrepancies between observed and simulated data.
The novelty of this approach is described as follows. Detailed data is available and statistical profiles are generated which contain properties of the network. A major novelty of the approach is that it overcomes limitations of current simulation models that although they concentrate on a global range of traffic networks and patterns, their calibration procedure is limited to only a few segments in the network using a pre-defined set of fixed value parameters. Dynamic updating of traffic statistical profiles based on changing parameter values in real-time improves calibration and accuracy. These profiles are fed to the simulation model to update the network parameters. These profiles also capture incidents such as accidents, lane closures, etc. which can be updated in the simulation model to give real-time status of the network. The parameters are adjusted accordingly, to simulate the effect of such events, which can be useful for traffic planners to take informed decisions.

Moreover, this process is repeated continuously so that a library of most current and historical data will be created and used by the traffic simulation model. It is expected that this will improve estimation and prediction of traffic conditions, and allow for more effective optimization of traffic control strategies in constantly changing traffic environments.

This Chapter provided the problem statement and discussed the current issues as well as the novelties that are proposed in this research. The next Chapter provides details of the proposed solution and framework used for the research.
Chapter 5

Proposed Solution

Traffic video obtained through cameras mounted on UAV give an “eye-in-the-sky” image of the network. This data can be exploited to derive considerable amount of detailed information about the traffic flow. Several traffic parameters are formulated and modified keeping in mind the information extracted using aerial video data.

The purpose of this research is to develop a system, which will optimize the traffic network, to improve the performance and flow of traffic at both normal and peak-hours. Also, it shows that the real-time images provided by the UAVs may help traffic planners to take better decisions in events of blockages caused because of events such as traffic jams or accidents. The focus of this project is to develop a system which would ensure efficiency of the use of current road infrastructure by optimizing traffic operations (traffic signals), influencing driver’s behavior by providing timely information (in case of accidents, detours), and providing real-time updated and calibrated simulation model predictions to traffic planners to take informed decisions. This information will give traffic planners the capability to make modifications to the system in case of accidents, emergencies, constructions, events etc. This would eventually lead to maximization of the capacity of the network and minimization of travel times and fuel consumption.

This work can be described and categorized into two main parts:

• Custom-made UAVs fly over certain intersection or link segment and collects real-time data using the cameras mounted on the UAV. This video data undergoes various image
processing algorithms to extract the environment details and gives information about traffic counts and trajectories.

- The above data is used to obtain statistically significant measures, which are then input into traffic simulation model to update the scenario of road usage and moreover, predict future trends based on current observations. All of this process occurs in real-time.

5.1 Framework

The proposed and utilized conceptual framework is shown in Figure 5.1. The real world traffic network block depicts the physical traffic network. The bold outline blocks depict the utilization of unmanned helicopters and the on-board/on-the-ground image processing system. Data is collected in real-time by cameras mounted on the UAV. This video data is converted into traffic data using the image processing algorithm described in the previous section. This data can be merged with data collected using other existing devices. Statistical profiles are generated using this raw data, which act as test parameters for traffic model. These parameters are then used for modeling traffic conditions. These test parameters are fed to the simulation model along with historical data. Once the model is calibrated to accommodate a current traffic pattern, measures of strategic effectiveness are incorporated to make improved decisions in real-time.
A real-time knowledge of traffic conditions is useful to generate traffic control and traffic information strategies. These strategies may prove beneficial to update signal control systems, decide whether new infrastructure is necessary to accommodate increasing traffic etc., and various other traffic related studies such as effect of percentage of heavy vehicles on the average speed and delay of the network etc.

5.2 Generating Statistical Profiles from Video

UAV-based video data has the advantage of providing an elevated 3D view of the environment. This spatio-temporal data provides microscopic details of individual vehicles and
network. Knowledge of time and position (space) of a vehicle allows for trajectory plotting and tracking of these vehicles. It is important for traffic planners to know the ratio of type of vehicles on a roadway to estimate network usage. The algorithm is used to identify and classify vehicles, distinguishes between cars, trucks, and bikes. The classification of different types of vehicles is necessary for traffic planning as increase in ratio of trucks and other heavy vehicles on a roadway decreases the average speed of the link. Thus, detailed information of vehicular classification is obtained using the image algorithm.

Traffic parameters are obtained using detailed video information. Consideration constraints posed by the requirement to accurately detect vehicles, observe the road and distinguish between overlapping / occluded vehicles, restricts observable areas. These constraints are taken into account when defining statistical profiles. An important aspect of the vision component is the identification of vehicular classification - of the ratio of type of vehicles on a roadway to estimate network usage; that is, identification of cars, trucks, emergency vehicles, motorbikes, etc. This is of major importance since an increase in ratio of trucks on a roadway decreases the average speed of the link. Some parameters are similar to formulations found in traffic flow theory literature, while others have been modified keeping in mind the information that can be extracted using aerial video data. Once the counts are determined using on-board / on-the-ground processing system, the statistical features can be calculated in real-time. It is advisable to perform the statistical calculations on the ground station due to high computing requirements, which require larger infrastructure than could be accommodated on the helicopter.

An urban network may be divided into links and intersections. The basic reason for differentiating links and intersections is that on links, vehicles interact only with other vehicles. That is, they need to change their behavior depending only on traffic flow or congestion. At intersections, vehicles also need to respond to signals and queue developments. As shown in Figure 5.2, intersection analysis will be used to calculate turning movement, queue estimation, and delay, while link analysis will be used to calculate speed, flow, and density.
Figure 5.2. Performance measures on a network (link and intersection).

The main performance measures that pertain to a link are speed, density, flow, volume, inter-vehicle spacing, occupancy, etc. Even though speed of each individual vehicle may be measured, mean speed is an essential parameter for traffic analysis.

Some of the traffic parameters can be obtained directly through the image processing algorithm such as count, volume, travel time; while other parameters have been derived using the methodology described below.

5.2.1 Acceptable Gap

The acceptable gap in a car-following behavior is the minimum distance between successive cars such that the latter car can safely drive at the same speed as the preceding car. Acceptable gap may be calculated using the video data based on Figure 5.3. Acceptable gap is essentially the distance between the rear of the leader vehicle and the front of the following vehicle.
The image algorithm determines the vehicles and encloses them into unique boxes. The distance between two successive boxes determines the gap between the vehicles. It is important to note that in a downtown area the acceptable gap is much smaller than elsewhere, but the idea is the same. Thus, the space headway between two vehicles in the same lane is calculated using equation:

$$h_s = l_1 + g_o$$  \hspace{1cm} (5.1)
Traffic trajectories can be obtained for individual vehicles based on the approach mentioned above. Each vehicle is assigned a vehicle id when it enters the network. The vehicle is followed through the network from the time that it enters the network till it exits the network. Using this trajectory, several important measures such as speed, volume, density, and average delay can easily be observed. Figure 5.5 shows the trajectories of four vehicles traversing through a network comprising of three segments. The dotted lines show the vehicle trajectories observed by conventional double-loop detectors. Such detectors are unable to find the delays occurring in the intermediate segments of the link. Using vehicle following, delays and travel time for each individual segment can be observed. Also, the density and flow can be observed for every segment in the link.
Using the above methodology, the mean speed, $s$, may be calculated by observing the travel time of individual vehicles through the link:

\[
s = \frac{d_i}{n \sum_{j=1}^{i} \sum_{j=1}^{n} \frac{1}{t_{i,j}}}
\]  

(5.2)

$d_i$ is the observable distance given by $d_i = VD_2 - VD_1$. The above equation aggregates all vehicles throughout all lanes while observing the time it takes for each individual to cover the distance between two consecutive VDs.

5.2.3 Flow

Flow, $f$, is given by the number of vehicles passing through a certain point in the network in a given time period ($T$). Any VD can be considered and the flow can be measured as the number of vehicles that passed the VD within a given time period:
Therefore, the dynamic occupancy of a link is defined based on the traffic flow $f$ and speed $s$ as follows:

$$o = \frac{f \times l_i}{s}$$

(5.4)

5.2.4 Density

Calculating density of a particular link or network has proven to be very difficult given that point detectors are unable to keep track of vehicles currently present on a link. Video data enables us to calculate density using spatial, temporal, as well as (pseudo)-spatial-temporal methods.

5.2.4.1 Spatial Density

Loop detectors are able to calculate spatial density only. Spatial density is calculated by the time of presence of vehicles on the stationary detectors. The same concept can be used to calculate spatial density using video data by placing a virtual detector of width $\Delta x$ at any point on the link as shown in Figure 5.6(a). The number of lanes assigned for this particular VD can be adjusted and the time taken by each vehicle to traverse this particular segment $\Delta x$ is noted. Using this process, the spatial density $k_s$ can be calculated as:

$$k_s = \frac{\sum_{j=1}^{L} \sum_{i,j} T_{i,j}}{T \times \Delta x}$$
5.2.4.2 Temporal Density

Another way to calculate the density of the network is to assign a certain region where the total number of vehicles present at a time is required to be observed. Temporal density is calculated using a Virtual Detection Frame (VDF) as shown in Figure 5.6(b). This method, in fact, uses a
single still-image at one time and calculates the vehicles present inside the \( VDF \). Using a \( VDF \) of length \( d_{fr} \), the equation for temporal density \( k_t \) becomes:

\[
k_t = \frac{1}{d_{fr}} \sum_{j=1}^{L} n_j
\]  
(5.6)

5.2.4.3 (Pseudo-) Spatial-Temporal Density

Based on the two calculated measurements, the spatial-temporal density may be obtained by repeating the procedure over a time period \( T \). Thus, temporal density is calculated for each time unit for a period of time \( T \) (for example: one hour), and the average density \( k_{s,t} \) can be calculated as:

\[
k_{s,t} = \frac{1}{T} \frac{1}{T} \sum_{j=1}^{L} n_j dt = \frac{1}{T} \frac{1}{d_{fr}} \int_{t=1}^{T} \left( \sum_{j=1}^{L} n_j \right) dt
\]  
(5.7)

5.2.5 Queue Estimation

The definition of queue length differs across literature. Several formulations are used by simulation models to implement queues [78]. For the purpose of our research, queue length at an intersection is defined as the number of “stopped” cars at an intersection at the instant the signal turns from red to green. At this time, the stopped cars start to dissipate, clearing away the queue. One of the problems with such definition is that it takes some time for the vehicles at the end of the queue to start moving, in which time some more vehicles enter the queue. The method described in this paper does not include these “moving” vehicles as part of the queue, as these vehicles do not stop due to the signal, but due to vehicular interaction only.
At the moment when the signal turns from red to green, a polygon-based area can be detected. Such type of analysis has also been used in [79]. Figure 5.7 shows one such scenario. The average spacing between two cars, or gap, at halt can be calculated prior to queue length estimation. This value can be taken directly from previous literature or an analysis of gap distance can be done for the particular intersection. Let $l_1$ and $l_2$ be the length of the polygon, and $w$ be the width of the total number of lanes. Also let $g_a$ be the mean acceptable gap between two vehicles. Thus,

\[ v = \frac{A}{(g_a + v_i) \cdot w} \quad (5.8) \]

where \[ A = \frac{1}{2} (l_1 + l_2) \cdot w \quad (5.9) \]

The above equation is helpful to find the total number of vehicles in queue in all lanes. The problem with such method is that even though the gap between adjacent vehicles in the same lane is considered, we ignore the gap between adjacent vehicles in adjacent lanes. To solve this, it is important to mention here that one vehicle actually blocks the area that extends till the boundary.
of the lane that it occupies. This rectangular region is represented as the product of the lane width and the length of the vehicle.

5.2.6 Turning Movement / Origin-Destination

It is essential for traffic planners to know an estimate of number of vehicles passing through an intersection. It is also necessary to know the ratio of turning vehicles (left, through or right) for signal timing and control purposes. Presently, turning movements are calculated using manual count only. This involves highly man-intensive task in which either several personnel have to stand at intersections for hours to collect data, or watch earlier captured video feed on their monitor and manually tabulate the entire data. This ratio can however be calculated by tracking every individual vehicle through an intersection, using the tracking algorithm. As mentioned earlier, $VDs$ are assigned at start and end points of links. Each vehicle in the network is tagged with its identity number, $vehicle\ id$, time of arrival and position at each $VD$ it goes through. For example, Figure 5.4 depicts an intersection with eight $VDs$ to record the movement of vehicles.

To illustrate the above point, a vehicle that enters the network through $VD_1$ and turns left will be assigned the path ($VD_1-VD_2-VD_7-VD_8$ and so on). $OD$ matrix is essential to analyze the travel behavior for a given network. $OD$ studies are beneficial for observing traffic patterns, as they are indicative of the driver’s preferred path from a specific origin to a specific destination.
Figure 5.8. (a) A network with multiple OD nodes (b) OD Matrix for small network.

Vehicles are tracked from the moment they enter the network until they leave it as shown in Figure 5.8 (a). Each node acts as both an origin and a destination. When a vehicle enters the network through a node, it gets tagged by its source of origin. Its path is followed using VDs as described above, and finally when it leaves the network, it gets assigned with the destination point. Travel time of each vehicle for every OD pair will be observed and tabulated. Assuming $n_{on,dn}$ be the number of vehicles with origin $o_n$ and destination $d_n$. Figure 5.8 (b) shows an instantiation of an OD matrix that can be formed from Figure 5.8 (a). Same type of table can used to represent the travel time $t_{on,dn}$ for vehicles to enter and exit the network. In case of large networks, each origin or
destination node for a zone will be considered as a centroid of the zone [80]. With current
technology, estimating this centroid point is not accurate. With help of aerial data, it will be easier
to accurately calculate centroid of the zone based on density of the zone.

5.2.7 Delay

Delay is a very important component of traffic behavior. A network with minimum delay
implies a free flow network with low travel times. Delays can be either recurrent (due to
bottlenecks, peak-hours) or temporal (due to an incident/accident etc). Delays can be accounted
due to increased occupancy of the network, which leads to speeds lower than free flow speed $s_f$. It
is rather very hard to calculate delays using conventional methods of loop detectors. Considering
that every vehicle is recorded for time and position through the network, delay may be calculated
as:

$$Delay = \frac{d}{s_f} - \frac{n}{\sum_{j=1}^{L} \sum_{i=1}^{n} \frac{1}{t_{i,j}}} - \frac{n*s_f}{\sum_{j=1}^{L} \sum_{i=1}^{n} \frac{1}{s_f t_{i,j}}}$$ (5.10)

Other parameters such as Level of Service (LOS) can also be determined. LOS indicates the
quality of service to travelers on a link. It is a qualitative measure of the operating conditions
based on speed, occupancy, travel time, convenience, etc. Less the time taken to travel, better the
LOS. Thus, if the density on a link is low, LOS is would be higher. The highway capacity manual
gives the following table to determine LOS if density is known.
Table 5.1: LOS measures. [81]

<table>
<thead>
<tr>
<th>Arterial Class</th>
<th>I</th>
<th>II</th>
<th>III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range of free-flow Speed</td>
<td>35 --&gt; 45</td>
<td>30 --&gt; 35</td>
<td>25 --&gt; 35</td>
</tr>
<tr>
<td>Typical free-flow Speed</td>
<td>40</td>
<td>33</td>
<td>27</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level of Service</th>
<th>Average Travel Speed (mph)</th>
<th>Delay (sec)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>&gt; 35 &gt; 30 &gt;25</td>
<td>&lt; 10</td>
<td>very short delay</td>
</tr>
<tr>
<td>B</td>
<td>&gt; 28 &gt; 24 &gt;19</td>
<td>10 --&gt; 20</td>
<td>short delays</td>
</tr>
<tr>
<td>C</td>
<td>&gt; 22 &gt; 18 &gt;13</td>
<td>20 --&gt; 35</td>
<td>significant delay</td>
</tr>
<tr>
<td>D</td>
<td>&gt; 17 &gt; 14 &gt; 9</td>
<td>35 --&gt; 55</td>
<td>congestion influential</td>
</tr>
<tr>
<td>E</td>
<td>&gt; 13 &gt; 10 &gt; 7</td>
<td>55 --&gt; 80</td>
<td>high delay</td>
</tr>
<tr>
<td>F</td>
<td>&lt; 13 &lt;10 &lt; 7</td>
<td>&gt; 80</td>
<td>over-saturated</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>LOS</th>
<th>Density</th>
<th>Speed</th>
<th>Flow Rate</th>
<th>Ratio</th>
<th>Max. v/c</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>10</td>
<td>55</td>
<td>550</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>16</td>
<td>55</td>
<td>880</td>
<td>0.39</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>24</td>
<td>55</td>
<td>1320</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>32</td>
<td>54.5</td>
<td>1744</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>45</td>
<td>50</td>
<td>2250</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>var</td>
<td>var</td>
<td>Var</td>
<td>var</td>
<td></td>
</tr>
</tbody>
</table>

Free Flow Speed = 55 mph
Table 5.1 shows the LOS categories along with the corresponding density, speed and flow rate at free flow speed of 55 mph. Similar tables can be found in the Highway Capacity Manual.

5.3 Statistical Methodology

Traffic parameters have been generated using above-mentioned equations. These profiles serve as inputs into simulation models to update the traffic parameters in real-time. Such procedure leads to better and optimized results from these models, which will improve the accuracy of simulated results as well as diminish discrepancies between observed and simulated traffic data.

It is essential that the output from simulation models depict the real traffic conditions. Calibration of simulation model involves adjusting model parameters so that the measure of effectiveness (MOE) such as volume, density, travel-time, delay etc. are at a reasonably accurate level as the real conditions. This problem can be viewed as a minimization problem: the minimization in the difference between the simulated results and the real world data.

The simulation model performs better (output replicates the real world traffic) based on proper calibration of MOEs. These MOEs differ for every simulation model, thus it becomes essential to identify the correct set of model parameters that affect the system performance significantly. In this work, two simulation models, CORSIM and Synchro have been used to analyze the effects of parameter variations on the output. The main goal is to find a set of parameter values so that the conditions given in the above equations are satisfied.

5.3.1 General Descriptive Statistics

The problem in hand is the continuous movement of traffic through a road network. The data is observed and collected in real-time, and is accumulated in discrete intervals of either five or fifteen minutes. Thus, the series consists of observations that are equidistant from one another in time and contains no missing observations. A time-series analysis approach is taken to identify
the properties of the data. Attempts have been made to statistically fit the data to develop useful models useful to understanding the characteristics of the underlying system. Depending on the nature of the data, averaging and smoothing techniques are performed. Several trends, if present, are identified.

A time-series dataset consists of various components such as seasonality, trends, cycles and other random fluctuations. Equation 5.11 is used to describe a time series event.

\[ Y_t = T_t + Z_t + S_t + R_t \]  \hspace{1cm} (5.11)

where \( T_t \) is the trend, \( Z_t \) is the non-random long term cyclic influence, \( S_t \) is the non-random short term cyclic influence, and \( R_t \) is the random deviation.

Depending on the duration of the dataset, several components of the time series can be identified and analyzed. In this current work, most of the data is obtained in real-time and due to constraints of flying time of the helicopter, only a short duration of data is available. This rules out identifying the seasonality and the long-term cyclic influence components.

The first step while performing any kind of statistical analysis is to plot the graph of the relevant data. A graph is useful to check the pattern of the series as well as to identify outliers as and missing values. Certain trends or effects due to other occurrences may be observed in these graphs.
Figure 5.9 shows the volume of traffic on a network for a week from Monday till Sunday. Data is accumulated every 15 minutes for the entire week starting at 12 am. By plotting a simple graph, it can be noted that the traffic trend for the weekend days of Saturday and Sunday is quite different from the weekdays. Also, the variation in traffic volume during peak hours can be observed as spikes in the graph. These graphs can be especially useful when an incident occurs leading to change in traffic conditions. It can be easily observed how the incident is affecting the traffic behavior.

A box-plot can also be plotted to observe the outliers as well as the distribution of observation points. Figure 5.10 shows the box-plot for traffic conditions during the entire week. The box-plot gives the average value of volume as well as the distribution of observation points. It can be observed that during the weekend, the traffic volume has less variation compared to weekdays. Also, the extreme values of volume during the weekdays correspond to peak-hour
traffic where the volume rises significantly. A similar box-plot of travel time or delay may indicate properties such as congestion and level of service on the network.

![Box-plot of traffic conditions during entire week.](image)

The next step is to obtain descriptive statistics on the data such as number of observations, mean, standard deviation, variance, skewness, and other relevant values. \( n \) is the number of sample observations.

Sample Mean:

\[
\bar{x} = \frac{1}{n} \sum_{t=1}^{n} x_t
\]  

(5.12)

Sample Variance:

\[
s^2 = \frac{1}{n-1} \sum_{t=1}^{n} (x_t - \bar{x})^2
\]  

(5.13)

Standard Deviation:

\[
s = \sqrt{\frac{1}{n-1} \sum_{t=1}^{n} (x_t - \bar{x})^2}
\]  

(5.14)
A subset of the above dataset was taken where only the northbound traffic was considered. The data consists of six hours of traffic between 9am and 3pm. Figure 5.11 shows the basic volume against time plot and the descriptive statistics obtained based on the observation points.

![Volume Vs Time Plot](image)

**Figure 5.11.** Volume vs time plot. Descriptive statistics of volume for given time period.

After obtaining the descriptive statistics, the next step is to using smoothing techniques to smooth out irregular fluctuations. Next section covers this topic in details.

5.3.2 Smoothing Techniques

Road traffic systems are highly non-linear in nature. The data observed through detection techniques may fluctuate quite significantly. The volume of traffic on a network may fluctuate depending on time of the day (peak hours/ off-peak hours), location (urban/rural/downtown), or
day of the week (weekdays/weekend). On initial investigations with the traffic trends, it was found out that Friday has a significantly different traffic pattern than either the other weekdays (Monday through Thursday) or weekend days (Saturday and Sunday).

Other factors affecting data could be missing data, outliers, or errors by the image algorithm to either miss cars or over-count the number of vehicles. In such cases, it is necessary to perform some kind of averaging/smoothing technique on the data before the simulation model can use the data. Some simple as well as advanced averaging methods are described below.

A dataset may contain three types of components: level, trend and seasonality. A level is considered if the data plot may be flat, but shows random fluctuations about some constant ‘level’. A plot may show an upward or downward ‘trend’ over trend. Finally, a plot may also indicate some seasonality.

5.3.2.1 Simple Average and Moving Average

A simple average is used as a baseline to describe fluctuations. This method is only used for preliminary description. A simple average ($\bar{y}$) can be calculated using

$$\bar{y} = \frac{1}{T} \sum_{t=1}^{T} y_t$$  \hspace{1cm} (5.15)

Moving averages is a mean of a constant number of observations. This mean is computed by a specific number of observations in a sliding time span that moves its point of origin one time period at a time. In case of simple moving average, each observation is given equal weight.

$$MA(n) = \sum_{t=n}^{T} y_t$$  \hspace{1cm} (5.16)
To illustrate this method, MA(3) would span through \( t1 \) to \( t3 \) and take the average of only these three readings instead of averaging the complete series. Other methods such as centered moving averages and double moving averages can also be used in case of long series.

### 5.3.2.2 Exponential Smoothing

Exponential smoothing uses weighted averages of the past data. This method assumes that the effect of recent observations is expected to decline exponentially over time. A simple exponential smoothing is used when the data plot indicates only the level component. This method is useful to isolate trends from irregular variation. Again to illustrate the point, if expected volume needs to be estimated at 11am, an observation taken at 9am has less influence than an observation taken at 10.45am. Exponential smoothing may be described by the following equation:

\[
MA_{t+1} = (1-\alpha)MA_t + \alpha x_t
\]  

(5.17)

where \( \alpha \) is the smoothing weight coefficient used for level component and lies between 0 and 1.

### 5.3.2.3 Holt’s Linear Exponential Smoothing

Simple exponential smoothing fails to account for trends in the dataset. Holt’s exponential smoothing method is used for series that also have a trend component along with the level component. Holt’s model uses the mean \( (\mu) \) of the series, smoothing weight coefficient \( (\alpha) \), trend coefficient \( (\beta) \), and trend smoothing coefficient \( (\gamma) \).

\[
Y_t = \mu + \beta t + e_t
\]  

(5.18)
Holt’s model continuously updates the mean and the trend coefficient by adding the trend coefficient to the previous intercept [83].

\[
\mu_t = \alpha Y_t + (1 - \alpha)(\mu_{t-1} + \beta_{t-1}) \tag{5.19}
\]
\[
\beta_t = \gamma(u_t - u_{t-1}) + (1 - \gamma)\beta_{t-1} \tag{5.20}
\]

5.3.2.4 Damped Trend Linear Exponential Smoothing

Another type of trend is a dampened trend that refers to a regression component for the trend in the updating smoothing equation. In this case, the lagged trend coefficients \(b_t, b_{t-1}\) are multiplied by a dampening factor \(q^i\)

\[
Y_{t+h} = \mu_t + \sum_{i=0}^{h} q^i b_t \tag{5.21}
\]

5.3.2.5 Winter’s Method

Winter’s method adds a seasonal parameter, \(S_t\) to the Holt model to account for both trend and seasonality.

\[
Y_{t+h} = \mu_t + \beta_t t + S_{t-p+h} + e_t \tag{5.22}
\]

where \(p\) is the periodicity of the seasonality, \(h\) is the number of periods into the forecast horizon that the prediction is being made. The updating equations for mean, trend and seasonality follows:

\[
\mu_t = \alpha(Y_t - S_{t-p}) + (1 - \alpha)(\mu_{t-1} + \beta_{t-1}) \tag{5.23}
\]
\[
\beta_t = \gamma(\mu_t - \mu_{t-1}) + (1 - \gamma)\beta_{t-1} \tag{5.24}
\]
\[ S_t = \delta(Y_t - \mu_t) + (1 - \delta)S_{t-p} \quad (5.25) \]

The data set is tested for the above methods to find the suitable smoothing technique. The root mean square error is chosen as the criterion for the selection of the smoothing technique. Other methods such as mean square error, mean absolute error and r-square may also be employed for selection criterion.

Calculated statistical profiles are fed to the simulation model. The simulation model will remain updated and will simulate real-time behavior as opposed to current methods when historical data is provided to the model. This will help in visualizing the current traffic pattern on the network, and in case of congestion, it will provide traffic planners with the opportunity to take quick decisions and employ dynamic traffic management techniques to deal with the problem. An incident will be able to be detected by sudden changes in behavior of the traffic pattern; for example, sudden increases in queue length may caution the traffic planners that some event is causing such disturbance. These real-time observations can be very useful in crucial circumstances.

5.3.3 Fitting Model Function

Once the data has undergone the smoothing process, the next step is to identify the model that represents the data. The process to identify the form of the model requires inspecting the data to estimate the autocorrelation, inverse autocorrelation and partial autocorrelation.

Autocorrelation function (ACF) is referred as the dependence of current observation on the previous observations of order k; k is usually called the lag. Autocorrelation coefficients measure the correlation between observations a certain distance apart. Autocorrelation at lag k can be found as:
\[ r_k = \frac{\sum_{i=1}^{N-k} (x_i - \bar{x})(x_{i+k} - \bar{x})}{\sum_{i=1}^{N-1} (x_i - \bar{x})^2} \]  

(5.26)

Correlogram, a plot between the autocorrelation coefficient \( r_k \) and the lag(k), can be plotted to check the correlation coefficients at relevant time lags.

<table>
<thead>
<tr>
<th>Lag</th>
<th>Covariance</th>
<th>Correlation</th>
<th>Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.012568</td>
<td>1.00000</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0.0091456</td>
<td>0.72771</td>
<td>0.200000</td>
</tr>
<tr>
<td>2</td>
<td>0.0084391</td>
<td>0.67149</td>
<td>0.286993</td>
</tr>
<tr>
<td>3</td>
<td>0.0072050</td>
<td>0.57330</td>
<td>0.344147</td>
</tr>
<tr>
<td>4</td>
<td>0.0054461</td>
<td>0.43334</td>
<td>0.380435</td>
</tr>
<tr>
<td>5</td>
<td>0.0044723</td>
<td>0.35686</td>
<td>0.399692</td>
</tr>
<tr>
<td>6</td>
<td>0.0027846</td>
<td>0.22157</td>
<td>0.412171</td>
</tr>
<tr>
<td>7</td>
<td>0.0018932</td>
<td>0.15064</td>
<td>0.416908</td>
</tr>
<tr>
<td>8</td>
<td>0.0006987</td>
<td>0.00556</td>
<td>0.419079</td>
</tr>
</tbody>
</table>

Figure 5.12. Correlogram showing autocorrelation against the lag.

Partial autocorrelation function (PACF) is an extension of autocorrelation where the dependence on the intermediate elements is removed. PACF are useful to see the serial dependencies for individual lags not biased or affected by other serial dependencies.
It is necessary to know if the dataset that is under observation is non-stationary. Most of the models described above assume that the data is stationary and work accordingly. A slow shift in levels in the data indicated in a data plot may indicate non-stationary series. Another good way of checking for non-stationary data is to check the ACF. A very slow decay in ACF indicates non-stationary series. Also, the Dickey and Fuller test for stationary may be performed.

A non-stationary series can be converted into a stationary series by differencing the series. Mostly only one level of differencing is sufficient, but occasionally the series has to be differenced twice to make it stationary. Another way to treat non-stationary series or a stationary data series is to perform log-normal transformation on it. The result is a normal data set that is useful for models that assume input data as normal or at least partially normal.

5.3.4 ARIMA Model

Box and Jenkins developed the Autoregressive Integrative Moving Average (ARIMA) model that combines the Autoregressive (AR) and Moving Average (MA) models. ARIMA models are useful in removing trends in the data. An ARIMA (p,d,q) model is composed of three elements: the autoregressive parameters (p), the number of integration or differencing passes (d), and the moving average parameters (q).
The autoregression process, ARIMA (p,0,0), relates the importance of previous observations to the current observation over time. The importance of previous observations decrease exponentially with time until the effect nears zero. Each observation in this case is a combination of a random error component and a linear combination of prior observations. A first order autoregressive process is given by

\[ y_t = \delta + \phi y_{t-1} + \varepsilon_t \]  

(5.27)

The moving average process (ARIMA (0,0,q)) is used for serial correlated data. The process is independent from the autoregressive process; each element in the series is composed of current random shock and parts of previous shocks. A first order moving average process is given by

\[ y_t = \mu + \varepsilon_t - \theta \varepsilon_{t-1} \]  

(5.28)

The autoregressive integrated moving average, ARIMA model is defined by

\[ \phi_p(B)(1-B)^d x_t = \theta_q(B)\varepsilon_t \]  

(5.29)

where p is the order of the autoregressive process, d is the order of regular differencing, and q is the order of the moving average process. The equations for the autoregressive and moving average are given by

\[ \phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p) \]  

(5.30)

\[ \theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) \]  

(5.31)
The identification of the ARIMA model for a given dataset is not straightforward as alternate models may also perform as well. It is necessary to make the dataset stationary before performing the ARIMA technique as ARIMA assumes that the data set is stationary. If a time series is non-stationary, a first order differencing or sometimes a second order differencing may be performed to make the series stationary. However, sometimes transformations other than differencing such as taking the logarithm of the original series are useful in reducing a non-stationary time series to a stationary one.

Akaike’s information criterion [84], AIC, is used to identify the best ARIMA model that fits the given dataset. The set of parameters for which the ARIMA model has the least AIC is considered the best model. The process of choosing the best model involves observing the plot of the series / differenced series, and correlograms of ACF and PACF. The series may require differencing to make it stationary. Pankratz [82] suggested some practical recommendations to select the correct parameters for ARIMA:

<table>
<thead>
<tr>
<th>Model Parameters</th>
<th>ACF</th>
<th>PACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1)</td>
<td>Exponential decay</td>
<td>Spike at lag 1; no correlation for other lags</td>
</tr>
<tr>
<td>AR(2)</td>
<td>Sine-wave shape pattern or a set of exponential decays</td>
<td>Spikes at lag 1 and 2; no correlation for other lags</td>
</tr>
<tr>
<td>MA(1)</td>
<td>Spike at lag 1; no correlation for other lags</td>
<td>Damps out exponentially</td>
</tr>
<tr>
<td>MA(2)</td>
<td>Spike at lag 1 and 2; no correlation for other lags</td>
<td>Sine-wave shape pattern or a set of exponential decays</td>
</tr>
<tr>
<td>AR(1), MA(1)</td>
<td>Exponential decay starting at lag 1</td>
<td>Exponential decay starting at lag 1</td>
</tr>
</tbody>
</table>
5.4 Simulation Model Selection

Several existing simulation models were reviewed and evaluated to explore which parameters were required for each model, and what types of outputs each model provides. The most common data inputs for above traffic simulation models are traffic counts, traffic signal control plans and basic simulation parameter settings. Most common output measures of performance include average volume, average speed, average queue length, delay time and travel time. Based on the ability of existing traffic simulation models on the flexibility on parameter modification, and the ease of output file analysis, SYNCRO/SimTraffic and CORSIM were selected to test the real-time calibration of the simulation models in this study. The research work required coordinating with the Hillsborough County traffic department that currently use SYNCHRO for their network modeling. Also, the available signal timing information format was compatible with SYNCHRO. Hence SYNCHRO was chosen as the primary modeling package for this research.

The commercial microscopic traffic simulation package, SYNCHRO/SimTraffic is used to realistically capture vehicle movement, queuing, congestion, signal timings, and other network patterns. Each model has its own comparative advantages and disadvantages. Following are the advantages of Synchro/SimTraffic (85):

- Synchro allows extensive adjustment of signal timing parameters.
- SimTraffic allows for adjustment of driver and vehicle characteristics (such as acceptable gaps, average speed etc.), and allows for specifications of driver populations.
- SimTraffic is easier to use and allows visual simulation of traffic movement.

To obtain good results from a traffic simulation model several steps are involved from identification of the observation area and obtaining the network geometry, to recognizing the traffic parameters governing the network behavior. The following steps were performed:

- Identify the link/intersection where the traffic surveillance and analysis need to be performed.
• Obtain network geometry including link lengths, number of lanes, speed limit, and storage lanes. These parameters can be obtained through the local transportation department or software such as Google Maps may be used.

• Input default values of network and traffic properties into the simulation model. Run the simulation model to compare the results of the model with real data.

• Update the simulation model with traffic parameters obtained through the statistical profile generation procedure. Re-run the model to check the discrepancies between the simulated results and the real data.

This Chapter provided with the proposed solution of the research. The conceptual framework of the research was defined followed by explanation of the proposed algorithm. Chapter six covers the details of simulation models and the process of model buildup and calibration.
Chapter 6

Results

Several experiments were performed during this research. Due to the limitations imposed by the FAA, the helicopter flights took place on campus. Currently, the flying time of these helicopters is limited to 30-45 minutes. These limitations put a constraint on collecting data for a longer period of time, as well as gathering data from multiple locations. It should be noted that these limitations do not limit the efficient of the approach. If, in future, longer sets of data are available, the same approach can be used to analyze and process the traffic data. Also, this approach is not limited to helicopter-based data collection only. This approach can be used for both unmanned helicopter-collected data as well as data collected through conventional detection methods.

In the experiments performed during this research, the unmanned helicopter is kept in a hovering state, that is, the source is fixed. Thus, only a certain region of the network is visible to the camera. The range of the network area certainly depends on the height of the helicopter, the pan angle of the camera and the quality of the camera. Traffic video obtained through this approach provides spatial-temporal data, which benefits in providing microscopic details of individual vehicles. By knowledge of time and position (space) of a vehicle, we can plot the trajectories of these vehicles. Such kind of information may be very useful in car-following studies. Data was collected using an unmanned helicopter with a fully autonomous pan-tilt vision system with one camera mounted on the helicopter hovering over the intersection of Alumni Drive and Leroy Collins Blvd. in the morning hour from 7:00 AM to 8:00 AM. Customized traffic
parameters are obtained based on each traffic network segment under consideration. Traffic is observed for all four directions and particular attention is made towards the turning movement of vehicles.

The image processing system involves the captured video to undergo several stages before the actual counts can be observed. The original image obtained through the camera needs to be filtered so that the algorithm is capable of identifying vehicle and obtain important parameters from the video. One of the capabilities expected from the algorithm is to identify as well as follow certain vehicles. In such cases, it is necessary that background disturbances do not interfere with this process. Thus, image processing becomes a serious challenge for this particular problem in hand. Several challenges and problems were faced during the image processing stage. Figure 6.1 shows the result of key processing steps involved. After background and road extraction, the video is segmented into regions containing motion, which are then designated by superimposing minimum bounding rectangles on them.
The background extraction faces some difficulty because there are too many unknowns. Compared to a statically mounted camera not only is our camera moving in three dimensions, but
also we have no data from the IMU to estimate its motion independently. It is also difficult to maintain track on a vehicle when it is being consistently occluded by another vehicle traveling towards the same direction at the same speed. We can cope with short duration occlusion. Selecting the counting zones is trivial in the case of the static camera but quite challenging in our case. As the helicopter moves the selected zones appear to move too. As a result the algorithm needs to track those as well which it does but not without error. Scaling issues that have to do with the fact that the pose of the camera with respect to the road is unknown. To put in simple terms, similarly sized cars maybe correctly detected as a single vehicle when they are far away but as two or more if the are close to the camera. Also, large vehicles tend to create multiple targets.

Virtual detectors are implemented as colored boxes in the image processing algorithm. Each lane has its own corresponding box, which is responsible for detecting every vehicle passing through it. The boxes can be either automatically placed after the system recognizes the road environment; or the experimenter can manually place the box to the desired detection region. It is critical that the boxes do not overlap the same region of interest, and the same vehicle should not be counted by both the VDs. Still, there can be exceptions when a vehicle tries to change lanes in the detection zone. Figure 6.2 illustrates how these detectors are implemented based on the proposed approach. The colored boxes show VDs for different lanes. It may be noted that because of instability factor of the helicopter, these boxes seem to be shifted across the lanes in the figure. This leads to one vehicle being counted by two detectors, which leads to vehicle count error. Further image stabilization will produce much better and accurate results.
Figure 6.2. Colored boxes show implementation of virtual detectors in the image processing technique.

Some direct parameters such as volume and speed can be observed through the algorithm. Currently, the algorithm has a tendency to overshoot the accurate count by about 10 percent, but an enhanced version of the algorithm currently under development will produce more accurate results. Figure 6.3 shows the volume and average speed on Alumni Dr. and Leroy Collins Blvd. Vehicle counts can be directly observed by the image processing algorithm. The figure shows the number of vehicles entering the network from all four directions and the average speed of the vehicles.
Figure 6.3. Vehicle entry counts, average speed on Alumni Dr. and Leroy Collins Blvd.

Just by looking at the input volume data and the turning movement of vehicles, it can be observed that the traffic follows a certain trend depending on the direction of travel. There is a significant difference in the number of northbound vehicles versus the southbound vehicles. Also,
since the data was collected on-campus, the average speed of vehicles was quite low. Since the data is for only one hour (due to limitation of flying time), and cover only one intersection, major deviations in traffic are not noticeable. Though, it has to be pointed out, that this effort is to show that important information can be extracted out from readily available video data. In the future, the flying time and the observable area can be increased massively.

Figure 6.4 shows the turning movement of vehicles on the observed area. The turning movement is observed by placing the VDs, as mentioned in earlier chapters. This parameter is very essential for the simulation model calibration, as well as choosing the appropriate signal timing.

Figure 6.4. Turning movement on Alumni Dr. and Leroy Collins Blvd.
Once the basic traffic counts are available, other important statistics are calculated for the data set. Volume and travel time are two most important parameters that are studied in detail. Since the procedure remains the same for each parameter, the complete steps for volume are included here.

Once the basic parameters of traffic are obtained, statistical profile is build up for the data set. As mentioned in Chapter 5, the first step performed is to plot volume against time. Figure 6.5 indicates that there is a steady upward trend. The plot also indicates that the series moves around a level. Since the data set contains only information about one day, seasonality is not a concern. Also, we will check for non-stationarity since the plot shows upwards trend.

![Volume Vs Time](image)

Figure 6.5. Volume plot for given data set. Each observation is taken at a 15-minute time step.

The second step is to use smoothing techniques on the data to compensate for outliers and missing data. It is possible that sometimes the detector is unable to count vehicles (or in our case, the image is unstable for a given time period) and we have a missing point of observation. Similarly, sometimes due to occlusion and other conditions, many vehicles get counted multiple times, thus resulting in outliers. The algorithm searches for the best smoothing method based on
the lowest RMSE value as shown in Figure 6.6. Root mean square error is considered as the criterion to select the best smoothing model.

<table>
<thead>
<tr>
<th>Model Title</th>
<th>Root Mean Square Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damped Trend Exponential Smoothing</td>
<td>35.62586</td>
</tr>
<tr>
<td>Linear (Holt) Exponential Smoothing</td>
<td>35.98788</td>
</tr>
<tr>
<td>Double (Brown) Exponential Smoothing</td>
<td>37.49782</td>
</tr>
<tr>
<td>Linear Trend</td>
<td>39.78014</td>
</tr>
<tr>
<td>Random Walk with Drift</td>
<td>44.43658</td>
</tr>
</tbody>
</table>

Figure 6.6. Smoothing techniques with relative RMSE.

The above mentioned smoothing methods are also plotted against the original volume data set for comparison. Figure 6.7 shows such plot with the best five models that fit the data.

Figure 6.7. Smoothing methods for volume data set.
The methods used here have been described in detail in the previous chapter. The best model that fits to this particular data set is the Damped trend exponential smoothing method. This again indicates that there is no seasonality in the data, while there is a trend as well as a level component that needs to be identified. Figure 6.8 shows the actual data plot along with the damped trend exponential smoothing method curve. The plot indicates that the damped trend exponential smoothing method fits the original series quite well.

![Damped Trend Exponential Smoothing](image)

Figure 6.8. Damped trend exponential smoothing for the given series.

ARIMA model was considered along with the other exponential models to check if ARIMA model performs better than the recognized Damped trend exponential smoothing model. Here are the steps involved in the model identification process:

- Check for stationary of the given time series. If the given time series is non-stationary, apply differencing to the time series to make the series stationary.
- For each set of (p,d,q) parameters, p + q ≤ 5, compute the AIC and choose the one with the smallest AIC.
• Determine the analytical equation for the chosen model.
• Plot the original and the predicted time series model.
• Plot the residuals for the predicted time series model.
• The final step is to show that the chosen model has the ability to forecast future values of the volume.

To model a series using ARIMA method it is necessary to make the series stationary. The best and easiest way to achieve stationarity is to difference the series. Sometimes a log-normal transformation may also be performed to make the data series normal but in our case it will not be very useful. This step involves checking for non-stationarity in the series. Augmented Dickey Fuller test is performed on the original series. Figure 6.9 shows that the test indicates very high significant probabilities on all lags, which corresponds to non-stationarity in the series.

Figure 6.9. Augmented Dickey Fuller test for stationarity on original data set.
The series is differenced once and again tested with the Augmented Dickey Fuller test. Figure 6.10 shows the volume plot and the result of the test on the series after first differencing. Now the series shows stationarity for lag 1 but has indications of non-stationarity at lag 2. Depending on the nature of the series, it is advisable to difference the series one more time and check for stationarity. Also, in most cases it is advisable to difference a series a maximum of two times.

Figure 6.10. Volume plot and Augmented Dickey Fuller test with first difference.
Since after first differencing there are still some signs of non-stationarity, the series is differenced a second time. Figure 6.11 shows the volume plot and the results of the Augmented Dickey Fuller test.

Figure 6.11. Volume plot and Augmented Dickey Fuller test with second difference.
After second differencing, the series looks to be stationary. To verify the stationarity, the ACF and PACF correlograms are drawn. Figure 6.12 shows these two correlations. It can be observed that the correlograms are consistent with a stationary series and do not show any evidence of a trend remaining in the series.

![Figure 6.12. Correlograms for ACF and PACF on second difference data set.](image)

The original series is differenced twice to get a stationary time series. Following the procedure above, the best model identified is a ARIMA(1,2,1) process where p=1, d=2 and q=1, with AIC=174.417. The analytical equation for the model is given by

\[(1 - \phi B)(1 - B)^2 x_t = (1 - \theta B)\varepsilon_t\]  \hspace{1cm} (6.1)

\[(1 + B^2 - 2B - \phi B^3 + 2\phi B^2)x_t = (1 - \theta B)\varepsilon_t\]  \hspace{1cm} (6.2)
Simplifying it, we get

\[ x_t - (2 + \phi_1)x_{t-1} + (1 + 2\phi_1)x_{t-2} - \phi_1 x_{t-3} = \epsilon_t - \theta_1 \epsilon_{t-1} \]  

(6.3)

For ARIMA(1,2,1), the one-step ahead forecasting model for the given data set is given by

\[ \hat{x} = 1.59686x_{t-1} - 0.19372x_{t-2} + 0.40314x_{t-3} = \epsilon_t - 0.89139\epsilon_{t-1} \]  

(6.4)

For the identified ARIMA model, the following plot in Figure 6.13 shows the original data vs the predicted values.

![Figure 6.13. Volume vs predicted values plot for ARIMA(1,2,1).](image)

As the above plot indicates, the one-step forecasting using the ARIMA(1,2,1) model is quite satisfactory. Figure 6.14 shows the ACF and PACF plots for ARIMA(1,2,1) model.
The next step is to examine the validity of the chosen model. This is done using residual analysis. The mean of the residuals, the variance, the standard deviation, standard error, and the mean square error, MSE are presented in the table below.

Table 6.1. Basic evaluation statistics for ARIMA(1,2,1).

<table>
<thead>
<tr>
<th>Mean</th>
<th>Variance</th>
<th>Standard Deviation</th>
<th>Standard Error</th>
<th>Mean Square Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.38031</td>
<td>1696.35</td>
<td>41.1867</td>
<td>8.58803</td>
<td>1651.60</td>
</tr>
</tbody>
</table>
Figure 6.15: Residual plot for ARIMA(1,2,1).

Figure 6.15 shows the residual plot for ARIMA(1,2,1). It is observed that all evaluation criteria support the quality of the proposed forecasting model. To check the capability of the identified model, the last 5 values of volume are hidden and we restructure the model and try to predict the following volumes only using the previous information. For example, we use the first 20 observations to forecast the 21\textsuperscript{st} value. Then we use the first 21 values to forecast the 22\textsuperscript{nd} value, and so on. Table 6.2 shows the actual, forecast and residual data for the last five values.

Table 6.2. Actual, forecast and residual data.

<table>
<thead>
<tr>
<th>Time</th>
<th>Original Values</th>
<th>Forecast Values</th>
<th>Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>14:00</td>
<td>687</td>
<td>691.8349</td>
<td>4.8349</td>
</tr>
<tr>
<td>14:15</td>
<td>774</td>
<td>742.1165</td>
<td>-31.8835</td>
</tr>
<tr>
<td>14:30</td>
<td>676</td>
<td>690.7371</td>
<td>14.7371</td>
</tr>
<tr>
<td>14:45</td>
<td>741</td>
<td>748.3754</td>
<td>7.3754</td>
</tr>
<tr>
<td>15:00</td>
<td>761</td>
<td>725.0905</td>
<td>-35.9095</td>
</tr>
</tbody>
</table>
Figure 6.16 below shows the plot of the original vs predicted values for the last 5 observations.

Figure 6.16. Original vs predicted values for the last 5 observations.

The final step remains to utilize the fitted model to predict and forecast future behavior of traffic. It is necessary in statistical analysis to define the upper and lower bound confidence levels. The default intervals used are 95% but depending on the accuracy of forecast requirements, a smaller region of error may also be obtained. The following plot in Figure 6.17 shows the forecast with 95% confidence interval. The upper and lower confidence levels are indicated.
The above mentioned technique is useful to check the traffic behavior in real-time. The statistical profile generation gives a good indication of the network properties as well as forecasts short-term traffic patterns. Once this profile is generated, the useful parameters are input into the traffic simulation model to both calibrate the simulate model as well as to make technical decisions based on the data.

Synchro is used to simulate a traffic network on the USF campus. The first step involved in simulation modeling is to build the traffic network model. Network geometry was obtained and validated using the Google Earth software, while special attention was paid to turning (storage) lanes. Synchro has a very nice feature of superimposing the image of the network that helps to precisely draw the links and intersections on the network. Figure 6.18 presents the real traffic network built using Synchro 6.
Figure 6.18. USF campus network using Synchro.

Data obtained from the video data is tabulated into standard UTDF format suitable for various traffic-related studies. Also, Synchro accepts UTDF files as input which makes it convenient to enter volumes. Traffic calculations for real-time data are done using a MATLAB code that takes directly the UTDF format data generated from real-time video at certain time intervals.

<table>
<thead>
<tr>
<th>DATE</th>
<th>TIME</th>
<th>INT</th>
<th>NBL</th>
<th>NBT</th>
<th>NBR</th>
<th>SBL</th>
<th>SBT</th>
<th>SBR</th>
<th>EBL</th>
<th>EBT</th>
<th>EBR</th>
<th>WBL</th>
<th>WBT</th>
<th>WBR</th>
</tr>
</thead>
<tbody>
<tr>
<td>10/12/07</td>
<td>7:05</td>
<td>1</td>
<td>7</td>
<td>28</td>
<td>1</td>
<td>1</td>
<td>32</td>
<td>0</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>6</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>10/12/07</td>
<td>7:10</td>
<td>1</td>
<td>8</td>
<td>24</td>
<td>3</td>
<td>3</td>
<td>43</td>
<td>7</td>
<td>6</td>
<td>5</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>10/12/07</td>
<td>7:15</td>
<td>1</td>
<td>10</td>
<td>17</td>
<td>3</td>
<td>2</td>
<td>56</td>
<td>25</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Figure 6.19. UTDF format.
Figure 6.20 shows the volume window for Synchro. The data can either be tabulated manually or by importing the UTDF formatted file. Default values of other parameters such peak hour factor, growth factor etc. are already provided in the volume window.

![Synchro Volume Window](image)

Figure 6.20. Synchro: Volume window.

Synchro requires a fixed deterministic volume for every approach to an intersection. Vehicles enter at a constant rate throughout the time period, which is not ideally the case in real-world scenarios. It is more realistic to introduce vehicles into the network using a non-constant approach. Several distributions of the vehicle headways can be incorporated based on the arrival pattern of vehicles. For example, CORSIM generates vehicle entry headways from a normal, negative exponential and Erlang distribution. By default, vehicles enter the system at a constant rate generated using a normal distribution. By analyzing the volume pattern of the real data, the correct distribution can be obtained such that the simulated model depicts the real-world data. Synchro by itself does not have an option to select vehicle entry distributions, but the parameters can be
adjusted in SimTraffic with different headway values for vehicles with speed under 20 mph, between 20 and 50 mph, and higher based on the driver behavior. Based on the formulas described above, the code builds a statistical profile as well as generates graphs. The updated parameters and MOEs calculated are input to the simulation model. Various parameters were adjusted in Synchro to observe their effects on the MOEs of the system. The most critical parameters of a simulation model to be adjusted are the peak hour factor, saturation flow rate, heavy vehicle percentage and gap acceptance. All these parameters change the behavior of the network dramatically and have to be appropriately chosen for the individual network. Since the network modeled in this research is on campus, we kept the peak hour factor constant to 1.0. The saturation flow rate was also kept constant based on previous studies. The heavy vehicle percentage and gap acceptance were calculated using formulas mentioned above.

These parameters are input into the lane window of Synchro. The lane window primarily is used to define the direction of flow and number of lanes per link. Parameters such as storage length are essential for the efficient performance of the model. Figure 6.21 shows the lane window and the adjusted parameters.
SimTraffic is the traffic simulation portion of the Synchro software package. Once the main parameters have been defined and the volume is input, SimTraffic visually simulates the network.

Figure 6.22 shows a snapshot of the animated traffic on one of the intersections of the network.
The advantage of simulation models is that they output several MOEs. These MOEs from different scenarios can be compared while deciding upon the best choice of scenario. Depending on the nature of the study, different MOEs are selected for optimization of the network. For urban networks, delay, speed and travel time are very important and significant output parameters. For interstate studies, travel time as well as LOS may be important parameters to observe. Figure 6.23 shows some of the output results from Synchro such as delay, travel time, average speed etc.

<table>
<thead>
<tr>
<th>Movement</th>
<th>EBL</th>
<th>EBT</th>
<th>EBR</th>
<th>WBL</th>
<th>WBT</th>
<th>NBL</th>
<th>NBT</th>
<th>NBR</th>
<th>SBL</th>
<th>SBT</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Delay (hr)</td>
<td>0.6</td>
<td>0.5</td>
<td>0.1</td>
<td>0.6</td>
<td>0.4</td>
<td>0</td>
<td>0.4</td>
<td>0.3</td>
<td>0.1</td>
<td>0.9</td>
<td>4.4</td>
</tr>
<tr>
<td>Delay / Veh (s)</td>
<td>38</td>
<td>29.5</td>
<td>8.5</td>
<td>38.3</td>
<td>22.6</td>
<td>3.4</td>
<td>30.9</td>
<td>17.8</td>
<td>12.9</td>
<td>22.3</td>
<td>21.4</td>
</tr>
<tr>
<td>Total Stops</td>
<td>65</td>
<td>54</td>
<td>28</td>
<td>64</td>
<td>46</td>
<td>11</td>
<td>40</td>
<td>52</td>
<td>51</td>
<td>20</td>
<td>107</td>
</tr>
<tr>
<td>Travel Dist (mi)</td>
<td>35.9</td>
<td>39.3</td>
<td>24.4</td>
<td>13.8</td>
<td>14.1</td>
<td>3.4</td>
<td>14</td>
<td>22.3</td>
<td>23.8</td>
<td>8.5</td>
<td>59.7</td>
</tr>
<tr>
<td>Travel Time (hr)</td>
<td>1.3</td>
<td>1.9</td>
<td>1</td>
<td>1.1</td>
<td>0.9</td>
<td>0.1</td>
<td>0.9</td>
<td>1.2</td>
<td>1.2</td>
<td>0.4</td>
<td>2.9</td>
</tr>
<tr>
<td>Avg Speed (mph)</td>
<td>19</td>
<td>21</td>
<td>26</td>
<td>13</td>
<td>17</td>
<td>24</td>
<td>16</td>
<td>23</td>
<td>22</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Vehicles Entered</td>
<td>58</td>
<td>64</td>
<td>39</td>
<td>62</td>
<td>62</td>
<td>15</td>
<td>50</td>
<td>83</td>
<td>85</td>
<td>22</td>
<td>151</td>
</tr>
<tr>
<td>Vehicles Exited</td>
<td>56</td>
<td>65</td>
<td>40</td>
<td>61</td>
<td>63</td>
<td>15</td>
<td>50</td>
<td>84</td>
<td>86</td>
<td>21</td>
<td>152</td>
</tr>
<tr>
<td>Hourly Exit Rate</td>
<td>224</td>
<td>260</td>
<td>160</td>
<td>244</td>
<td>252</td>
<td>60</td>
<td>260</td>
<td>388</td>
<td>344</td>
<td>84</td>
<td>688</td>
</tr>
</tbody>
</table>

Figure 6.23. Synchro results.
An important part of calibrating a simulation model is to choose the correct value of parameters that correctly replicate the properties of the road network. After the network was built for Synchro, various runs were performed to observe the change in MOEs depending on network properties. Parameters such as lost time, headway and acceptable gap are varied to observe the significance of variation on the MOEs. Other parameters such as driver behavior, aggressiveness, peak hour factor, turning speed etc. may also be varied depending on the information available to the user. It was observed that lost time and acceptable gap do not have significant effects on the output of this model. The headway, which was changed through SimTraffic accounted for variations in vehicle entry as well as delays as shown in Figure 6.24.

![Variation in Delay wrt Headway](image)

![Variation in Volume wrt Headway](image)

Figure 6.24. Variation in delay and volume w.r.t. headway.

Statistical validation is performed which includes goodness of fit measures to observe the similarity (or discrepancy) between the real and simulated systems. Single-value MOEs are considered for validation to summarize the performance of the system since only a small section of the network is observed (helicopter is in hovering state). As mentioned in Chapter 5, RMSE is chosen as the goodness of fit to evaluate the overall performance of the simulation model. In the context of model validation, the RMSE may be defined as
\[ \text{RMSE} = \sqrt{\frac{1}{n-1} \sum_{n=1}^{N} (Y_{n}^{\text{sim}} - Y_{n}^{\text{obs}})^2} \]  

(6.5)

where \( Y_{n}^{\text{obs}} \) and \( Y_{n}^{\text{sim}} \) are the observed and simulated values respectively. Another common measure used to obtain relative error is the Theil’s inequality coefficient, \( U \):

\[ U = \frac{\sqrt{\frac{1}{n} \sum_{n=1}^{N} (Y_{n}^{\text{sim}} - Y_{n}^{\text{obs}})^2}}{\sqrt{\frac{1}{n} \sum_{n=1}^{N} (Y_{n}^{\text{sim}})^2} \sqrt{\frac{1}{n} \sum_{n=1}^{N} (Y_{n}^{\text{obs}})^2}} \]  

(6.6)

Relative error measures may also be informative and interpretable. Mean Percentage Error (MPE) is given by

\[ MPE = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{Y_{i}^{\text{sim}} - Y_{i}^{\text{obs}}}{Y_{i}^{\text{sim}}} \right) \times 100 \]  

(6.7)

Mean Absolute Percentage Error (MAPE) is another relative measure given by

\[ \text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{Y_{i}^{\text{sim}} - Y_{i}^{\text{obs}}}{Y_{i}^{\text{sim}}} \right| \times 100 \]  

(6.8)

Each experiment of SimTraffic was simulated for 30 runs. Parameters such as speed and travel time are considered as MOEs. The observed real-time values are aggregated for every 15 minutes. The results from simulation model are also tabulated for every 15 minutes to validate the model.
and check for discrepancies in the network. Following are the results obtained for the average speed observed from the real network and the simulated model.

Table 6.3. Goodness of fit statistics.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>2.154</td>
</tr>
<tr>
<td>U</td>
<td>0.053</td>
</tr>
<tr>
<td>MPE</td>
<td>-1.57%</td>
</tr>
<tr>
<td>MAPE</td>
<td>10.57%</td>
</tr>
</tbody>
</table>

The resulting statistics show that the simulation model replicates the real system quite accurately. The error measures are quite small, proving that the model has been calibrated well. Forecasts observed through statistical methods may also be accommodated into the simulation model as inputs to get a better and improved model.

Overall, the algorithm is able to extract vital information from real-time data and is helpful to develop simulation models capable of replicating the real system more accurately. Future work related to this work is discussed in the following Chapter.
Chapter 7

Conclusion and Future Work

7.1 Conclusion

This research discusses issues such as traffic surveillance and traffic simulation modeling and proposes the use of unmanned helicopters to obtain detailed traffic information in real-time. Unmanned helicopters are custom-made equipped with vision system and pan-tilt capabilities to follow vehicles. Real-time spatial-temporal video data is collected and converted in useful traffic measures. Further, an approach is presented to generate statistical profiles of obtained data, which provides traffic engineers valuable information about the traffic characteristics required to make informed decisions. A traffic simulation model is set up in Synchro/SimTraffic using accurate network geometry and signal timing information. This model is further calibrated based on parameters obtained through the statistical procedure. Results show that the followed approach is suitable to obtain vital information about the traffic pattern as well as the use of such information is utilized to develop more accurate simulation models, which can be used by traffic engineers for taking informed decisions.

7.2 Future Work

This research presents a novel approach to extract vital traffic information in real-time. This work can be expanded in many ways based on the requirements of the study. Currently, only one intersection or part of the link can be observed due to limitations of the flying time as well as flying altitude. Better flying time along with helicopters flying at a higher altitude with better
cameras would give a better perspective of the network. In direct context of using unmanned vehicles for traffic surveillance, future work needs to be done with multiple helicopters hovering on different intersections collecting data simultaneously. The combined data needs to be input into the simulation model to generate an overall profile of the traffic network. Also, work needs to be done on calculating statistics when the helicopter is in a moving state, that is, the image source is also moving.

Multiple MOEs capture the spatial-temporal distribution of traffic characteristics. This method may be used for validation when multiple helicopters collect data simultaneously such that the dynamics of the network could be captured. These MOEs consist of flow or speed at different locations and travel times at different links/sections of the network.

Depending on the nature of study and availability of detailed information, relationship between several variables may be obtained using regression analysis techniques. For example, the current algorithm is able to differentiate between the different types of vehicles. A regression analysis approach may be used to observe the effect of heavy vehicles on speed/travel time/delays of the network. A similar study may utilize logistic regression analysis techniques to predict the probability of occurrence of congestion on a network in case of incidents or special events.

Last but not the least, future work needs to be done by utilizing the current approach in emergency situations such as evacuations, accidents, incident management etc. An analysis of real-time behavior of traffic may be utilized to make decisions to de-route/re-route traffic in case of accidents and evacuations, change signal timings and plans, informing emergency vehicles of the quickest/shortest path and many other applications.
References


Appendix A. Nomenclature Used

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h_s$</td>
<td>Space Headway</td>
</tr>
<tr>
<td>$g_{a}$</td>
<td>Acceptable Gap</td>
</tr>
<tr>
<td>$d$</td>
<td>Link length</td>
</tr>
<tr>
<td>$l_i$</td>
<td>Length of $i$th vehicle</td>
</tr>
<tr>
<td>$n/N$</td>
<td>Number of vehicles currently in the network</td>
</tr>
<tr>
<td>$f$</td>
<td>Flow</td>
</tr>
<tr>
<td>$s$</td>
<td>Mean Speed of vehicles in network</td>
</tr>
<tr>
<td>$L$</td>
<td>Total number of lanes</td>
</tr>
<tr>
<td>$t_{i,j}$</td>
<td>Travel time of the $i$th vehicle in the $j$th lane</td>
</tr>
<tr>
<td>$T$</td>
<td>Total time period under observation</td>
</tr>
<tr>
<td>$n_j(t)$</td>
<td>Number of vehicles in lane $j$ at time $t$</td>
</tr>
<tr>
<td>$s_f$</td>
<td>Free flow speed</td>
</tr>
<tr>
<td>$k_s$</td>
<td>Spatial density</td>
</tr>
<tr>
<td>$s_{i,j}$</td>
<td>Speed of $i$th vehicle in the $j$th lane</td>
</tr>
<tr>
<td>$k_t$</td>
<td>Temporal density</td>
</tr>
<tr>
<td>$k_{s,t}$</td>
<td>(Pseudo-) spatial-temporal density</td>
</tr>
<tr>
<td>$\Delta x$</td>
<td>Width of Virtual Detector</td>
</tr>
<tr>
<td>$d_{fr}$</td>
<td>Length of Virtual Detection Frame</td>
</tr>
<tr>
<td>$n_j$</td>
<td>Number of vehicles in the $j$th lane</td>
</tr>
<tr>
<td>$on$</td>
<td>Origin node</td>
</tr>
<tr>
<td>$dn$</td>
<td>Destination node</td>
</tr>
<tr>
<td>$n_{on,dn}$</td>
<td>Number of vehicles with origin $on$ and destination $dn$</td>
</tr>
<tr>
<td>$t_{on,dn}$</td>
<td>Travel time for vehicles with origin $on$ and destination $dn$</td>
</tr>
</tbody>
</table>
About the Author

Anuj Puri received his Bachelor’s Degree in Electrical Engineering from Nagpur University, India in 2001. He came to the U.S. in 2002 and graduated with his Masters degree (M.S.) in Computer Science from Purdue University in 2004. He entered the Ph.D. program at the University of South Florida in Fall of 2004. While in the Ph.D. program at the University of South Florida, Anuj worked with the Unmanned Systems Lab (USL) and Center for Urban Transportation Research (CUTR) on traffic analysis and the development of statistical profiles based on unmanned helicopter-based video data.

While in the Ph.D. program at the University of South Florida, Mr. Puri has published numerous pieces of work on intelligent traffic analysis. His research interests encompass intelligent transportation systems, traffic analysis and simulation modeling.