An Approach to Counting Vehicles from Pre-Recorded Video Using Computer Algorithms

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AN APPROACH TO COUNTING VEHICLES FROM PRE-RECORDED VIDEO USING COMPUTER ALGORITHMS

A Thesis

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering

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The Department of Civil & Environmental Engineering

by

Mishuk Majumder
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ABSTRACT

One of the fundamental sources of data for traffic analysis is vehicle counts, which can be conducted either by the traditional manual method or by automated means. Different agencies have guidelines for manual counting, but they are typically prepared for particular conditions. In the case of automated counting, different methods have been applied, but You Only Look Once (YOLO), a recently developed object detection model, presents new potential in automated vehicle counting. The first objective of this study was to formulate general guidelines for manual counting based on experience gained in the field. Another goal of this study was to develop a computer program for vehicle counting from pre-recorded video applying the YOLO model. The documented general guidelines provided in this project can be useful in acquiring the required standard and minimizing the cost of a manual counting project. The accuracy of the automated counting program was found to be about 90 percent for total daily counts, although most of that error was a consistent undercounting by automated counting.
Chapter 1. Introduction

1.1. Background

Urbanization refers to a process where many people move from rural areas to urban areas, which leads to a continuous increase in population. The United Nations in 2009 and the International Organization for Migration in 2015 both estimated that around 3 million people worldwide are moving to cities every week. This increase in the number of people adds to the demand for infrastructure development for accommodation and other facilities such as recreation, education, health, etc. As a result, land is continuously being developed for purposes such as residential and industrial buildings, commercial complexes, recreational facilities, and so on. These developments require new transportation links to provide access to the existing transportation network. Consequently, trips are being added to the network by new developments all the time.

The increasing number of trips is the source of different problems in urban areas such as traffic congestion, delay, traffic accidents and so on. Dealing with these kinds of problems is a great challenge for transportation planners because the transportation network is a dynamic and complex system that changes with the continuous development process. Transportation planners must analyze this system to evaluate current and forecast future problems to provide better facilities to road users. Moreover, they monitor different components of the transportation system, for example, traffic volume and density on individual links of the system. The fundamental data that transportation planners require to analyze and monitor the transportation system is traffic count data.

Before constructing a new development, the owner or developer must get approval from the relevant authority that the new development can be accommodated within the existing system
and to ensure that users of the facility are adequately catered for in terms of access and parking. In this approval process, the role of transportation planners is significant as they analyze the feasibility of the new development in terms of trips. Transportation engineers conduct a traffic impact study (TIS) to analyze the feasibility of a development. According to the Vermont Agency of Transportation Policy and Planning Division Development Review and Permitting Services, TIS is an evaluation of the congestion and safety effects of a particular development on its surrounding and supporting transportation infrastructure. Based on this evaluation, transportation planners decide whether the project will be approved as is or whether a new road development is required. One of the parts of TIS is to study existing traffic on a road network and estimate future traffic to analyze congestion, where the main input is traffic counts. Therefore, traffic counts are essential data to conduct a TIS successfully.

Traffic counts involve the enumeration of vehicles traveling on a roadway section or at an intersection. There are two methods of traffic counting: manual and automatic. Manual counting is the most common method. On the other hand, automatic counting is based on technology and is increasingly being used.

There are mainly two methods for manual counting in the current era: on-site traffic counts and counts from the pre-recorded video. The on-site traffic counts refer to counting traffic on the site by trained individuals. The number of individuals required for counting may vary depending on the number of lanes, traffic volumes, speed of vehicles, and weather conditions. On-site traffic counting provides immediate count data because trained individuals report counts in real-time. Manual counting from pre-recorded video refers to counting traffic from site video footage. In this method, cameras are installed on a site to record traffic movement. After recording, videos are
downloaded from the cameras and stored on a server. Finally, traffic counting is conducted from the stored videos by trained individuals.

Manual counting from pre-recorded video performs better than on-site counting in terms of repeated counting, safety, and unfavorable weather condition. Manual counting from the pre-recorded video can be repeatedly checked to find the error in counts, while on-site counting does not provide that possibility. During the night, on-site counting may not be safe or convenient because this method requires the physical presence of the observer on the site to conduct counting. Moreover, on-site counting is difficult to perform during unfavorable weather conditions such as heavy rain, high temperature, snow, and fog. In contrast, manual counting from pre-recorded video only requires the individual’s presence on the site for the time taken to install and retrieve cameras. Traffic counting is conducted from recorded videos at the office. So, it is apparent that manual counting from the pre-recorded video is more convenient, safe, and a more accurate method than on-site counting.

Although manual counting from the pre-recorded video can provide total and classification counts at any time interval, it is a time-consuming method. Depending on the quality of video footage, the volume of traffic, the speed of vehicles, traffic composition, and the number of lanes, each hour of video can take up to 3 hours to count (Stofan 2018). If video footage contains a large volume of traffic, individuals have to report more counts that take more time. High-speed vehicles do not allow individuals to increase the speed of a media player, which results in more counting time. Besides, more variation in traffic composition and more lanes increase counting time. Thus, while working on the ITE trip estimation of an area, a sample of sites can be selected to make it economical and faster. Many factors may lead to deteriorating the quality of counting data, such as the selection of sites for surveying, the selection of time and survey instruments, team
management and so on. Proper planning before a survey can decrease the effect of these factors and increase the accuracy of counts.

The main elements of planning are the selection of the sites and survey instruments, scheduling of fieldwork activities, team management, and counting. Sites are selected based on different factors such as the type of site, the population density of a survey area, type of adjacent roads and so on. Survey instruments should be selected carefully because the quality of the instruments influences the quality of video data. For example, a good resolution camera helps individuals to recognize vehicles and report counts correctly. The volume of traffic fluctuates depending on the time, the type of the area, the class of road and so on. So, the time and duration of a survey should be selected in a way so that count data adequately represents the entire range of trip behavior of a survey site. Proper team management facilitates fieldwork and reduces the cost of a survey. So, it is good practice to follow guidelines of manual counting surveys to perform efficient manual counting.

Guidelines give an initial idea about the procedure of fieldwork and manual counting. Different agencies and institutions have guidelines for manual counting, but those are for specific locations and conditions. For example, the New York State Department of Transportation (NYSDOT) has guidelines for fieldwork where they considered factors such as type of area, population density, and weather, which are based on New York only. So, their guidelines are not applicable to any location other than New York state. Automated counting can be categorized into two types: applying in-situ technologies and computer algorithms. In-situ technologies refer to counting traffic using detectors located along the roadside (Leduc 2008). There are different types of detectors in current use, such as pneumatic road tubes, piezoelectric sensors, magnetic loops, microwave radar, and so on. These detectors can count arriving and departing vehicles in any
roadway section. These technologies can be costly, and their accuracy depends on factors such as weather (rain, fog, sun, and wind), the volume of traffic, types of roads and so on. A better alternative to these methods is using computer algorithms, which involve counting traffic automatically from pre-recorded video.

There are different traditional models for applying computer algorithms to count traffic. The basic procedure of all models is the application of the image processing technique (Joseph 2018). The traditional background subtraction method (Stauffer 2009) and the sequential Monte Carlo method (Li 2002) are common methods for image processing. The first step of these models is detecting objects in each frame of a video. Different models use different techniques for detecting objects; for example, the background subtraction method separates moving objects from the background of an image applying the pixel change technique. The next step is tracking detected objects from frame to frame using different trackers such as the Kalman box tracker. Most of these traditional object detection models are slow, cannot classify vehicles, and have low levels of accuracy. However, recently a few pre-trained neural network object detection models have been developed, which are more effective than traditional methods for vehicle counting.

Currently, there are three popular modern object detection models available; they are the Faster R-CNN, SSD, and YOLO models. They are pre-trained to detect a few default objects. These models can be operated on the OpenCV platform (a library for implementing computer vision algorithms). Any programming language can be used at the desired interface of the models, but C++ and Python are the most popular programming languages used in computer vision analysis. The YOLO object detection model is the most effective and popular model in current use (Karagiannakos, 2019)
You Only Look Once (YOLO) is a recently developed pre-trained object detection model. It is the most effective model in terms of speed and accuracy, and since speed and accuracy are the most critical factors, YOLO is the most suitable model for vehicle counting from pre-recorded videos. Moreover, transportation planners require directional vehicle counts, which is an added requirement beyond just vehicle recognition. Counting in time intervals is also a factor to consider because many projects need traffic data for different time intervals, for example, at 5 or 15-minute intervals. Applying these features to the counting capability of the YOLO object detection algorithm is one of the objectives of this thesis.

1.2 Problem Statement

Following manual counting guidelines can be helpful in achieving the required success of a survey. However, current guidelines on manual counting are not general, i.e., they are applicable to a particular territory and condition only. Thus, the first goal of this research is to formulate general guidelines for manual counting surveys in general.

There is no actual ground to estimate errors in manual counts without conducting repeated counts. But conducting repeated counts for all sites increases the cost and time of a project. This research proposes a few formulas for estimating errors where repeated counts for a sample of sites are considered as true counts.

Manual counting is costly and time-consuming. Many technologies are available in this modern era that can be good alternatives to manual counts, but these technologies are expensive and have many limitations. A possible solution to this situation may be developing computer algorithms to count traffic from pre-recorded videos. But, the accuracy of most of the current algorithms is not at a satisfactory level. Also, the algorithms do not provide counts in a flexible time interval. This study develops algorithms to apply the YOLO object detector to conduct counts
from pre-recorded videos. The accuracy level and flexible interval counts make the developed automated counting method an improvement on other algorithms.

1.3. Objectives

1. Develop guidelines on manual counts at individual land-use sites using pre-recorded video footage.
2. Develop an automated vehicle counting method of vehicle arrivals and departures at individual sites.
3. Compare the accuracy of the automated method with the manual counts.
Chapter 2. Literature Review

The literature review is comprised of two sections: a manual counting section, and a programming-based automated counting section. The manual counting section focuses on limitations of ITE trip estimation, adjustment of ITE trip estimation, The 6Ds and mode choice, and accuracy and economy of manual counts. The automated counting section focuses on the functions, suitability, and limitations of different methods of vehicle counting applying computer algorithms. It also includes the feasibility of different object detection models based on their accuracy and processing speed. In addition, the development of YOLO (You Only Look Once), a pre-trained object detection model, is discussed at length.

2.1. Manual Counting

Manuals of different agencies

The New York State Department of Transportation (NYSDOT) has guidelines to perform manual counting. It has an agreement with different local agencies to conduct short-duration traffic counts. They provide equipment and a manual on how to conduct the counts. The manual stipulates to count a different minimum number of short duration counts for different local agencies. According to the manual, they choose random samples from all local roads to get aggregated statistics of traffic counts. The purpose of this approach is to get a consistent traffic count. Random sampling is performed uniformly from local roads so that the samples can represent all local roads and provide a consistent count. Also, all traffic counts are in 15 minutes intervals, at least 48 hours of data are required while 72 hours are preferable, volume counts are done based on direction, and classification counts are conducted with respect to lanes. NYSDOT uses these short-duration counts for different traffic studies.
The Texas Department of Transportation (TxDOT) has different traffic data collection programs, which are automatic traffic recorder volume data, accumulative count recorder traffic data, highway performance monitoring system traffic data, five-year count program, vehicle classification data, truck weigh-in-motion data, vehicle speed data, long-term pavement performance data, and border trend traffic data. For each type of program, they have a selected number of sites and predefined duration for traffic data collection. For example, an automatic traffic recorder volume data program has 160 permanent sites in the state, and the counts are conducted 24 hours a day and 365 days annually. They use different technologies for collecting traffic counts, such as permanent automated traffic recorder, sensors, loop, piezoelectric sensors and so on.

The Florida Department of Transportation (FDOT) has 300 continuous traffic data collection sites throughout the state. According to their manual, traffic data may include daily counts, vehicle classification, speeds, weight, directional factor, and truck factor depending on the location of a site. The manual also recommends short duration traffic counts which are conducted by district personnel at thousands of sites in the state. Generally, traffic data is collected from January through December each year.

The Minnesota Department of Transportation (MnDOT) collects traffic counts on highways, county state-aid highways, county roads, and municipal state-aid streets. MnDOT also uses a short duration traffic count method. There are 32,000 classified short duration traffic survey sites in the state, and the typical duration of traffic counts is 48 hours. They use factors on raw short-duration counts to get traffic counts by season and traffic composition. The formula they use to get adjusted traffic counts is as follows.
Adjusted Count = Raw Traffic Count x Seasonal Adjustment Factor (SAF) x Axle Correction Factor (ACF) (Trucks Only).

In addition, MnDOT collects traffic volume on 1200 sites for vehicle classifications. They have different technologies for collecting traffic counts. Their 80 automated traffic recorders installed in the pavement collect traffic data with vehicle classification. Also, 17 weigh-in-motion sites collect vehicle volume and characteristics data, i.e., weight, type, and speed data. In addition, they have more than 240 counting sites, which are operated by the Regional Traffic Management Center aims to collect volume data.

The Oregon Department of Transportation has different guidelines for different types of counts; for example, intersection classification counts and peak hour counts. Intersection counts provide vehicle classification and individual vehicle movement. The typical duration of counts is 16 hours. The duration remains at 16 hours when vehicle classifications, turn movements, multiple peak periods, truck classifications, signal warrants, air quality, and noise studies data are required. For peak hour counts, the duration is 3 hours. When more than one peak hour counts are necessary, it is recommended to collect 16-hour counts. For road tube counts, a 48-hour count is preferred. According to the Oregon Department of Transportation, the old counts can be used to estimate future traffic counts, but they follow a few conditions to re-use the data. If no significant development occurs, three to five years old data can be used to minimize the cost. The 30th highest hour volumes (30 HV) should be used to represent future volumes of traffic. The volume of traffic, which will be reached 30 times or exceeded 29 times in a year, is called the 30th highest hour volume. The counts should be taken as close to the likely 30th highest hour as possible to get a typical traffic mix of the 30 HV for the analysis. It typically requires collecting counts on a weekday afternoon (usually in summer) in larger urban areas but may include weekends for high...
recreation areas (the coast or Central Oregon), or areas experiencing lunch hour peaks, or high reverse direction flows during the day.

The National Cooperative Highway Research Program (NCHRP) has produced guidelines for collecting traffic data. Their guidelines are divided into three parts: planning program, implementing a program and adjusting counts. According to their guidelines, planning of a program includes specifying the data collection purpose, identifying data collection resources, selecting general count locations, determining the count timeframe, and considering available counting methods and technologies. Implementing the program includes obtaining permission from site owners, selecting counting devices, inventorying and preparing devices, training staff, installing and validating equipment, calibrating devices, maintaining devices, managing count data, cleaning and correcting count data, and applying count data. For conducting counts, it recommends different technologies such as weigh-in-motion and sensors. The report recommends short-time counts if time is short and sufficient equipment is not available for long-duration counts. It recommends counting classified traffic, pedestrian, and bicycle volumes individually. After conducting counts, it recommends adjusting counting data, which includes applying correction and expansion factors. Correction factors are applied to adjust raw data to true ground values. Expansion factors are applied to short-duration counts to estimate traffic volume over long periods of time.

According to the Center for Transportation Research and Education (CTRE) at Iowa State University, a manual count is necessary when equipment for automated counting is not available or affordable. On-site automated counting methods such as pneumatic road tubes, piezoelectric sensors are faster than manual counting, but the cost of the necessary instruments is high. However, according to CTRE, the typical duration of a manual count is less than a day. Standard time
intervals for counts are 5, 10, or 15 minutes. Counts are typically conducted on Tuesday, Wednesday, or Thursday because Monday morning and Friday afternoon show an exceptionally high volume of traffic. They use three methods to record manual counts: tally sheets, mechanical counting boards, or electronic counting boards. Before conducting manual counts, a checklist is highly recommended by them. The checklist includes the details of a selected survey location, survey time, and availability of relevant instruments for fieldwork.

**Limitations of ITE trip estimation**

Many research studies have been conducted on ITE trip estimation, where the most common practice of trip estimation is based on vehicle counts and characteristics of an establishment. For example, according to the study of Schneider et al., ITE’s trip-generation rates typically relate vehicle trip counts to measures of building size (e.g., gross square footage, number of units) for a particular land-use classification. There are many other factors that significantly control trip estimation model, but their level of significance can vary depending on the characteristics of a survey area. For example, population density may not be a significant factor in a rural area, but in an urban area, it may be significant on trip generation due to high population density compared to a rural area. Therefore, it is challenging to find the factors that must be taken into consideration for a trip estimation model. As a consequence, many researchers found different limitations of the ITE trip estimation model while applying for different conditions.

According to Westrom et al. (2017), one of the most common problems of the ITE trip estimation procedure is that it only counts vehicle trips related to developments and does not consider pedestrian trips. In a broad sense, the ITE trip estimation procedure assumes that the arrival and departure of a person in an establishment only occur by vehicle, and ITE ignores all non-vehicle trips. Consequently, when analysts ignore the impacts of transit, pedestrian
infrastructure, bicycle facilities, and urban settings on vehicle-trip generation, vehicle trips are overestimated (Clifton 2012). This overestimation of vehicle trips leads to vehicle-oriented development, which increases vehicle miles of travel (VMT) and increases environmental pollution as well.

However, Schneider et al. (2015) recommend using this overestimated suburban trip in case of smart-growth developments. Although this recommendation ignores ITE guidelines, it is effective for smart-growth developments because it prescribes wider roads, and more turning lanes, parking and vehicle facilities that help to accelerate development. In contrast, it is not economical in the aspect of engineering because it leads to unnecessary developments and discourages non-vehicle-oriented design.

Later ITE guidelines were relaxed regarding the view that activity at a site could be measured by the number of vehicles visiting the site alone. ITE 2004 guidelines state that the trip rate based on vehicle counts obtained at suburban locations that may or may not have transit or bicycle and pedestrian facilities should not be used for land-use projects in urban areas near transit and easy walking distance from other land uses. The final report of trip generation data collection in urban areas (2014) recommends counting the people entering and exiting established developments. In addition, a more recent version of the ITE trip estimation manual (2017) has included person-based trip data rather than vehicle-based data to decrease the overestimation of vehicle trips.

The location where counts are conducted also affects the ITE trip estimation. According to Currans, ITE data collection has been based predominantly on suburban trips for more than fifty years. Due to this suburban bias, the model is, strictly speaking, not applicable to the urban area.
So, the ITE trip generation manual, 9th edition, recommends adjusting trip rates for urban areas where non-vehicles trips are significant.

The accuracy of the ITE trip estimation is not the same for different land uses. Many research studies have been conducted to compare the ITE predicted trips and the actual trips of different land uses, where most of the research indicates that there is a difference in the estimations of trips. For example, according to Clifton et al., the greatest range of error in ITE’s estimation of vehicle trips occurs in the central business district, urban core, or downtown areas, followed by mixed-use development. In addition, this study shows that error occurs both in over and underestimating vehicles for retail and residential uses.

**Adjustment of ITE trip estimation**

Different research studies have been conducted to adjust under or overestimation of ITE trip estimation for different land uses. Some researchers adjusted the ITE trips by using a few rules, for example, increasing or decreasing the estimated trips to a percentage based on the characteristics of land uses. Some researchers adjusted the trips using local trip data. Other researchers worked with transferring the ITE trip estimation model to different land uses.

Clifton et al. (2015) examined how the urban context affects vehicle trip generation rates across three land uses: high-turnover restaurants, convenience markets, and drinking places. The goal of the study was to adjust the ITE vehicle trip rates based on built environment characteristics in those three land uses. An intercept travel survey was performed to collect count data for analysis in the study. They developed nine models that aim to predict adjustment to ITE trip rates, where each model was dedicated to a single measure such as activity density, number of transit corridors, and so on. Their developed adjustment models estimate improved trips to the ITE’s trip rates for
convenience markets and drinking places, but the models performed similarly to ITE trip estimation for restaurants.

Schneider et al. (2015) developed two linear regression models, one for an A.M. peak-hour and one for a P.M. peak-hour, to adjust ITE trip estimates to produce more accurate vehicle trips for developments in smart growth areas. They used different variables in their models, including variables responsible for lower trip estimation in smart growth areas, such as residential population density, employment density, transit service, and metered on-street parking. The results of the adjustment model show that the models are only appropriate for planning-level analysis at sites in smart-growth areas. In addition, the method is only appropriate for single land uses in several common categories, such as office, mid- to high-density residential, restaurant, and coffee/donut shop. Although they used the data and conditions for California, the models can be applied in any smart growth area in the United States.

Currans and Clifton (2015) conducted a household travel survey for adjusting ITE estimates for the urban context. In this study, three adjustments were estimated for eight general land-use categories. In addition, a “pooled” category was included, where all travel survey data were considered. The findings of the study show that the three adjustments provide similar results to more complex adjustment methods. Moreover, the “pooled” land-uses category adjustments also provide similar results to the more detailed segmentation of travel survey data.

The 6Ds and mode choice

The built environment is the man-made establishment of land uses and transportation networks of an area. These features have a direct influence on the travel demand and mode choice of an area. In travel demand studies, the original measures of the built environment (BE) are “three Ds,”; density, diversity, and design (Cervero and Kockelman 1997) followed later by destination,
accessibility, and distance to transit (Ewing and Cervero 2001, Ewing et al. 2009). The sixth D is demand management, which includes parking facilities and their cost (Ewing and Cervero, 2001).

Automobile dependency is a critical challenge to transportation policymakers and urban planners, which happens partly due to low-density development and poor integration of land use (Ogra and Ndebele, 2014). Due to automobile dependency, walking and bike trips decrease, resulting in more vehicles on the road and an increase in vehicle miles of travel (VMT). In order to address this issue, urban areas need to be designed to allow high-density development complemented by mixed land use and investment in easily accessible public transportation (Hui et al., 2013, Jun et al., 2013 and Dempsey et al., 2012). The main assumption of high-density development is placing residential buildings near major transport nodes, amenities, and workplaces to increase the convenience of overall daily demands that support sustainable transport modes such as public transit and walking (Kenworthy and Laube, 1999, and Buys et al., 2011). High-density development results in destinations such as retail facilities and jobs being closer, which leads to an increase in walking trips (Forsyth et al., 2007; Lee and Moudon, 2006). Moreover, high-density shortens trips (i.e., with activities closer together, more trips occur within a community), inducing non–motorized travel (i.e., walking, bike) and increasing high occupancy travel (i.e., public transport and ride-sharing) (Cervero, 2003). Collectively, these outcomes decrease vehicle mile travel of an area.

Diversity (land-use mix) measures how many types of land use, for example, offices, residences and retails, are available within an area (Frumkin et al., 2004). In a broad sense, diversity represents the number of different lands uses in a given area and the frequency of those land uses. For example, if residential buildings are considered a land-use, then the total floor area of the residential buildings in a given area represent the weight of residential land use in the
estimation of diversity. One way to measure land-use diversity is to use entropy (Ewing and Cervero, 2010). A low entropy value represents a single-use environment where a high value indicates diverse land-uses. Diverse land uses have a great impact on travel behavior and trip rates. For example, diverse land use near transit links decreases vehicle trips and increases convenience for the community, i.e., a person can go shopping, buy dinner, pick up children from the daycare center and come back home using transit. So, it is evident that land-use diversity ensures optimum use of land and convenience to the community.

Design refers to the design of a transportation network that describes the degree to which destinations are connected by streets (Leslie et al., 2007). Transportation networks may vary from highly interconnected dense urban grids links to sparse suburban links of curving streets (Ewing and Cervero, 2010). Measures of design include average block size, the proportion of four-way intersections, number of intersections per square mile, safe and smooth accessibility to transit stations (for example, accessibility by walkways and cycle paths), and amenities such as benches, parks, landscaping, and libraries (Suzuki et al. 2013; and Ewing and Cervero, 2010). So, the design of a transportation network can influence mode choice and trip rates. For example, a bike-friendly design, i.e., more bike lanes and fewer roadway intersections in bike routes, is likely to increase the number of bike trips. A design that allows easy access to the transit from the community is also likely to increase transit ridership.

Destination accessibility refers to the convenience of access to trip attractions (Handy, 1993). It can also be defined as the number of jobs or other attractions reachable within a given travel time, which tends to be highest at central locations and lowest at peripheral ones (Ewing and Cervero, 2010). The accessibility to a central business district is mainly measured by the distance to it. The goals of destination accessibility are premised on the logic of ensuring greater mobility
by moving people around the city more swiftly, not by bringing urban activities closer together (Suzuki et al., 2013 and Sivakumaran et al., 2014). In this regard, the transit system is a reliable model to provide access to a wide variety of destinations such as work, service centers, recreation, and so forth (Ogra and Robert, 2015). Bus Rapid Transit (BRT) is another transportation mode that can provide efficient and quick movement of passengers to destinations, increase transit ridership, and increase trip attractions to developed and underdeveloped areas (Wirasinghe et al., 2013). Transit systems can move large numbers of people to destinations at a time and they typically occupy a small space on the road, thereby reducing congestion. All these facilities increase the trip attraction of an area, which results in the development of that area.

Distance to transit refers to the average shortest distance from residents or workplaces of an area to the nearest transit station or stop. It is a significant measure that controls the passenger demand of a transit system. Moreover, it helps to evaluate existing transit services, allocating transportation investments, and making decisions on land development (Mamun et al., 2013).

Demand management refers to any activity, method, or program that reduces vehicle trips, resulting in more efficient use of transportation resources (Tal et al., 2011 and Rahman et al., 2010). The policy for demand management can be considered in two contexts, which are actions that are implemented at specific sites (e.g., rideshare programs at an employment site), or strategies that are implemented at an area-wide level (e.g., growth management policies for a state or community, or the implementation of an area-wide variable work hours program) (Meyer et al., 1999).

**Accuracy and economy of manual counting**

It is known that manual counting is the most accurate method to get traffic counting data. However, since the counting is conducted by humans, there may be errors in the counts. According
to the research conducted by Zhenga and Mike (2012), total counting error in manual counts is usually less than 1 percent, and classification error between 4 and 5 percent. The main reason for classification error is the failure to detect the length or form of vehicles accurately. In addition, when individuals use a media player to count traffic from pre-recorded videos, an increase in video speed may lead to failure to record or classify vehicles correctly.

Scheduling in a manual counting survey is an important factor that can influence the quality of counting data. Sharma (1983) conducted manual traffic counts throughout the year to determine the most effective time. According to his findings, short period traffic counts are the most effective method. However, the accuracy of the short period counts depends on the type of road that will be surveyed, and the hour-to-hour traffic variation on the same day. The month of the year, the day of the week, and the duration of traffic counts also influence the result. The highest accuracy is expected for commuter sites and the least in highly recreational sites. His research also showed that for 8 hours or less on weekdays, a period with a midpoint at 3:00 or 4:00 p.m. is expected to provide the most accurate volume estimates for each class of road. The advantage of including this period is that peak hour turning movements and vehicle classification can be observed because the counting period includes the evening peak traffic.

Transportation agencies often conduct short period traffic counts and then apply factors based on weekday, seasonal variation, road type, and so on to estimate AADT. Research conducted by Granato (1998) shows that applying these factors can reduce the error of AADT estimates by one-quarter.

Sometimes manual counting is not a suitable method for traffic counts. Kusimo and Okafor (2016) show that automated surveys are preferable for long-period traffic surveys. In the case of long-period manual surveys, human error is a major factor that leads to an error in counts. Video
recording is not preferable at night because visibility is often impaired, and it becomes difficult to
detect vehicles accurately. In addition, the security factor of individuals and instruments is a
question for manual counting surveys at night.

2.2. Automated Counting

Research on automated counting

One of the conventional methods of object detection is applying the background subtraction method, which involves separating the moving part of the image from the entire frame being analyzed. The background subtraction method can be applied in different ways depending on the modeling of each pixel of the image. For example, Ridder et al. (1995) modeled each pixel of the background applying a Kalman filter to identify which pixels belong to the background and which do not, while Wren (1997) modeled the background using a single Gaussian value to estimate the probability that a pixel belongs to the background or not. However, these initial types of background subtraction methods have many limitations, such as not being robust when video footage contains shadows, low light, light changes, and slow-moving vehicles. In addition, the video processing speed of most of those methods is too slow for practical vehicle counting. To overcome these problems, Stauffer and Grimson (1999) modeled each pixel as a mixture of Gaussian values, i.e., each pixel is modeled as a mixture of values. The initial step of their method is to divide each frame into several pixels. The next step is to model each pixel of the image following a few rules. If the source of a pixel is a single lighting surface, a single Gaussian is used to represent the pixel. Practically, in the view frustum (i.e., the image captured by the camera) of a particular pixel, multiple surfaces can appear, and lighting conditions on the surface can change. In this case, they used a mixture of so-called adaptive Gaussians to approximate this process. Adaptive Gaussians are values that can change with the changes in the condition of a pixel. Each
pixel of a video frame is modeled in this manner. In the following frame of a video, the Gaussian values for the pixels that do not match with the pixel values of the previous frame are grouped using connected components. In this process, the moving objects are separated from the background, i.e., the detection of an object is performed. The connected components, i.e., detected objects, are tracked from frame to frame to evaluate its direction of movement. However, this method is slow and does not perform well for overlapped and large objects. Besides, this method can only detect objects but cannot classify them.

A rule-based system (RBS) uses rules to analyze and interpret data. Typically, a series of questions are posed in sequence to allow an answer to be inferred. The basis of the system is that an inference engine deduces an outcome based on the responses to individual questions. Cucchiara et al. (2000) used image processing and rule-based reasoning for vehicle tracking on visual data. Their method is capable of tracking vehicles during the day or night. This method operates in two steps: a formal separation of objects from the entire frame using a low-level image processing module, and then tracking vehicles from the scene using a high-level module. Generally, an image frame is comprised of two parts: the target vehicle and the surrounding objects such as houses, trees, lanes, parked vehicles, etc. Masking of the frame is a good practice to separate a target vehicle from surrounding objects, but this does not fully separate the target vehicle, especially when the vehicle stops (e.g., for a red traffic signal) for a certain amount of time. So, it is challenging to separate parked, and temporarily stopped vehicles. Here, the motion of a vehicle is used as a discriminating factor to extract a target vehicle. In daytime conditions, a Spatio-temporal analysis is next conducted to detect and track vehicles. In this case, the word spatial refers to the consideration of illumination variation in the zone where motion is detected, and temporal defines the extraction of moving zones in the frame. The bottom line is that during the day, the Spatio-
temporal module extracts the blocks of pixels that move from frame to frame. Their algorithm considers three consecutive frames to detect moving pixels. In this way, the vehicles are detected and tracked during the day. A high-level knowledge-based system is used to count vehicles, which separates the moving, stopped, and road-crossing vehicles for the desired vehicle counting purpose. In this module, they use a production-system model which is based on data-sensitive rules, i.e., rules for entry or exit of vehicles, stopped vehicles, crossing vehicles and each rule must be satisfied to consider the vehicle as a valid count.

At night, they use an analysis technique called the morphological analysis of headlights. At first, algorithms use the image masking procedure to separate headlight pairs of an image from surrounding objects such as street lamps, highly reflected road markings, parked vehicles, etc. The image masking technique makes the frame simpler, but it does not fully separate the headlight pairs. The headlight pair of individual vehicles are separated by thresholding the image, which is a method for segmenting images. Then, the separated headlight pairs are matched with headlight templates. The headlight pairs that match the templates are considered vehicles. However, at night, this method cannot detect vehicles that have only one headlight, for example, a motorcycle. In addition, this method cannot classify vehicles.

Li and Chellappa (2002) used a sequential Monte Carlo method for tracking and verifying objects. This method is a broad class of computational algorithms that rely on random sampling. The detection and tracking of objects are accomplished in three steps. First, the current state of an object is determined based on its position, velocity, and density. Second, sequential importance sampling (SIS) is used to identify objects in a particular frame. In this stage, SIS algorithms approximate the dynamic density of an object with proper weights to detect an object. These algorithms can keep track of slow-moving objects, which cannot be detected in most of the
background subtraction models. Third, the object is tracked from one frame to another frame and verified as a target object. In this step of the SIS algorithm, tracking is conducted by setting the state ‘x’ to some parametrization (for example, the location of the object) of objects, which is determined in the first step. The posterior probability estimation process is applied to verify an object. This process is a conditional probability where the background, i.e., the part of the image which does not move, is considered to validate the object. The results suggest that the algorithm provides a promising approach for tracking and verifying objects.

Classification of objects and removing unwanted shadows in an image are a great challenge in an automated traffic surveillance system. Hsieh et al. (2006) used the novel line-based shadow algorithm to solve these problems. In the first stage, vehicles are extracted from the background using image differencing. Then a vehicle histogram is compiled by accumulating the number of vehicles passing a particular point. Lane dividing lines are obtained using these histograms. However, each extracted vehicle is passed through a shadow elimination process to reduce shadows to a minimum level. In the shadow elimination process, two kinds of lines are drawn to eliminate unwanted shadows and detect vehicles. One line is drawn parallel, and another line is drawn perpendicular to the lane dividing line. A Kalman filter is used to track vehicles, which is accomplished based on the position and motion of the vehicles. The next step is to classify objects. Through line fitting and connected component analysis, the length and size of the vehicles are obtained. These two features are applied to categorize vehicles into different classes. This approach is a good method to track and classify vehicles. In the shadow elimination process, lane dividing line features are used instead of color features, which makes the method more accurate.

The most recent technology in the object detection field is the application of Convolutional Neural Network (CNN) based object detectors. Chauhan et al. (2019) developed computer
algorithms for vehicle classification and counting in non-laned road traffic using this technology. They used three CNN based object detection software frameworks: YOLO, Tensorflow Mobilenet-SSD, and Caffe Mobilenet-SSD. They applied a pre-trained open-source model to detect and classify vehicles. The open-source data sets they use are MS-COCO, PASCAL VOC 2007, and KITTI. But, from their model, class-specific accuracy values were found to be low for cycles, trucks, and pedestrians.

The YOLO object detection algorithm is deployed in Darknet, which is an open-source neural network framework written in C and CUDA. So, applying the YOLO algorithm in Python is difficult. On the other hand, the machine learning software TensorFlow is coded in C++, but it can be applied using C++ or Python. So, if the YOLO weight file can be converted to TensorFlow format, the weight file can be deployed using Python. Wizyoung (2019) has shown how to convert the YOLO weight file to the TensorFlow format. Tensorflow, OpenCV-python, and tqdm were used in his model to convert the YOLO weight file to the TensorFlow format. Some codes and directories were used for this convention.

**Development of YOLO**

An object detector performs two activities: object detection and object recognition. An object detection algorithm identifies objects that are present in an image. The input of an object detector is the whole image, and the output is the class label and the probability of being a valid object. On the other hand, the object recognition algorithm evaluates the type and location of an object in an image. Sub-regions of an image are selected to find the position of an object. Then the object recognition algorithm looks for the object in the image and identifies the boundaries of the object in a bounding box. The bounding box describes the height, width, and dimensions of the detected object.
The Sliding Window method is an easy way to generate sub-regions of an image. In this method, every sub-region of an image is selected by a box or window and classified by an object recognition model. Object recognition models are trained at a specific scale or a range of scales. This method works well for fixed aspect ratio objects, i.e., 2D projection or 3D images. However, it is expensive when images are searched for at different aspect ratios. In addition, selecting the sub-regions and training the model is time-consuming.

A good alternative to the Sliding Window method is the Regional Proposal method. The input to this algorithm is an image, and the output is bounding boxes that divide the image into different sub-regions. These sub-regions are the potential location of objects in an image. The sub-regions, i.e., the bounding boxes, are described in terms of individual confidence values. Bounding boxes with low confidence values are eliminated, and bounding boxes with high confidence values are proposed as containing the detected object.

R-CNN, Fast R-CNN, and SSD are recent object detection algorithms. R-CNN and Fast R-CNN use selective searches to classify objects. Fast R-CNN can be applied using the Regional Proposal algorithm. Redmon and Farhadi (2016) developed a different object detector called YOLO, which feeds the image once through the network and identifies the objects. SSD also forwards the image through a deep learning network, but YOLO is faster than SSD, and the accuracy is also higher. YOLO uses the non-maximal suppression technique to process an image, which is an outstanding technique compared to other detectors. At the beginning of this technique, YOLO divides an input image into a 13 x 13 grid of cells, which is a default value in the YOLO program. Then, each cell predicts several bounding boxes in the image, where each bounding box represents a single potential object. Afterward, the YOLO algorithms estimate a single probability value for each bounding box, i.e., potential objects. The acceptance of a bounding box as a valid
object detection is controlled by a threshold value. It is a variable input value of the YOLO detector that stands in the range 0 to 1 and acts as a filter for bounding boxes. For example, a threshold value of 0.25 means that the bounding boxes which have a probability value of 0.25 will be accepted as valid object detection, and other bounding boxes will be eliminated due to low probability value. However, when a threshold value is provided to the YOLO algorithms, it filters the bounding boxes and shows the detected objects.

2.3. Summary Of Literature Review

Individual agencies have their own guidelines for traffic data collection and conducting counts. Most of the agencies have permanent sites for collecting traffic data throughout the year. The duration of traffic data collection varies with the agency and location of the site. Agencies encourage the use of short-period counts that are expanded using an expansion factor.

Although the most common method of trip estimation at individual sites is using the ITE trip estimation method, it has some limitations. For example, it only counts vehicle trips related to the development and does not consider pedestrian trips. As a consequence, the non-vehicle trips are ignored, and vehicle trips are overestimated, which leads to unnecessary development. The later versions of the ITE trip estimation include person-based trip data rather than vehicle-based data to decrease the overestimation of vehicle trips. In addition, different studies have been conducted to adjust the under or overestimation of ITE trip estimation for different land uses. However, the built environment (BE) has a direct impact on travel demand and mode choice. The original measures of the built environment are density, diversity, and design.

Different studies have been conducted to evaluate the error and economy of manual counts. In most of the cases, it was found that errors of total counts are less than 1 percent. The accuracy of counts also varies with the selection of sites, quality of equipment, and time of a survey.
There are different traditional methods for detecting an object on an image, such as the background subtraction method, a rule-based system (RBS), and the sequential Monte Carlo method. One of the problems in vehicle detection is unwanted shadows. Different methods have been developed to remove the shadows. There are different modern object detectors available for vehicle countings, such as Faster R-CNN, SSD, and YOLO. In terms of accuracy and speed of processing, YOLO performs better than other object detectors. YOLO uses the non-maximal suppression method to detect an object in a video frame. YOLO vehicle counting allows directional vehicle counts, flexible time interval counts, and vehicle classification.
Chapter 3. Methodology

The methodology of this research is addressed in two parts: [1] Formalizing the manual count procedure, [2] Developing a new computer algorithm to count vehicles from pre-recorded video applying the YOLO object detector on the Tensorflow platform and using the Kalman Box Tracker to track vehicles. It also includes an evaluation of the accuracy of automated counting. The approach applied in the methodology is shown in figure 3.1. The research approach consists of two tasks: task 1 and task 2. Task 1 describes the steps of fieldwork and conducting traffic counts manually. Task 2 reflects developing algorithms for automated traffic counting and analyzing videos to count traffic automatically.

Figure 3.1. The Research Approach of Manual and Automated Counts

3.1. Manual Counting

This section introduces the procedure of site, time and camera selection, office preparation, and execution of fieldwork aimed at the collection of video data. In this study, 40 sites were selected in southern Louisiana for the collection of video data. A few criteria were
followed for the selection of sites, time of the survey, and cameras. At the office, the schedule of the survey work, preparation of a checklist, and work distribution were conducted. On a typical survey day, cameras were installed at the entrances and exits of each site to record the movement of vehicles. After the fieldwork, the recorded video data were used to count arriving and departing vehicles to each site by a 5-minute time interval.

**Selection of sites and time**

The survey was conducted in the metropolitan areas of Baton Rouge, Lafayette, and Hammond in Louisiana by request of the sponsors of the research project, the Louisiana Department of Transportation and Development. From these metropolitan areas, forty strip malls were selected for the survey. First, a sampling frame of all strip malls in the survey area was established. Then each strip mall was characterized as having either a high or low surrounding land use diversity, population density, and traffic intensity. This resulted in each site being categorized into 1 of 8 groups. Five sites were then randomly selected from each group, resulting in 40 sites being selected for manual and automated counting in the survey.

The selection of survey time refers to the scheduling of fieldwork, i.e., the selection of the season, day, and hour. During the summer, people go on vacation, and schools remain close. During the winter, weather can affect travel, and it coincides with several holidays such as Thanksgiving, Christmas, and New Year. So, the best time to conduct a survey is in Fall or Spring. Fall was selected for the survey because it best fitted with the project schedule. The entire survey was conducted prior to the COVID-19 pandemic.

Businesses generally have steady customer demand throughout the weekdays, except for Fridays, and particularly Friday afternoons. Thus, Monday through Thursday was selected for the
survey period. The survey was conducted for two consecutive days for each site to capture the full diurnal and day-to-day variation in traffic at a site.

The hours of the survey were selected based on the opening and closing hours of strip malls and the convenience of camera installation. The average opening and closing hours of most of the strip malls were 8 AM and 6 PM, respectively. So, 8 AM to 6 PM was selected as the period in which to conduct the survey each day. Cameras were installed before 8 am on the first day of a survey and retrieved after 6 pm on the following day.

Selection of cameras

The cameras were selected based on resolution, battery life, and weather factors. The resolution of a camera is an important factor that controls the success of automated and manual counting. One of the objectives of this research was to use pre-recorded videos for automated counting. Here, the success of automated counting depends on the quality of the video, as determined by the resolution of the camera. Good quality video increases the accuracy of manual counts because it enables individuals to recognize and report counts confidently. So, in this study, the minimum resolution of the cameras was considered as 480 pixels (frame size 480 x 640 pixels), which ensured a good quality video. Battery life was selected based on the duration of the survey. Since this project was required to record videos continuously for two days, the minimum battery backup of the cameras was selected to be a minimum of 40 hours. The weather factors were also considered for the selection of the camera. It was ensured that the cameras were able to operate in bad weather, for example, rain and fog.

Three types of cameras were selected in this research primarily for their properties but also due to their availability from other prior projects conducted by LTRC. The configurations of these cameras are shown in table 3.1.
### Table 3.1. Configuration of Cameras

<table>
<thead>
<tr>
<th>Camera Name</th>
<th>Scout Video collection</th>
<th>Counting Camera</th>
<th>CountCam2 Traffic Recorder</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Miovision</td>
<td>CountCam</td>
<td>CountingCars</td>
</tr>
<tr>
<td>Weight (lbs)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Resolution (pixels)</td>
<td>640</td>
<td>480 x 640</td>
<td>480 x 640</td>
</tr>
<tr>
<td>Storage (GB)</td>
<td>64 GB and extendable</td>
<td>Extendable</td>
<td>64 GB SDXC internal storage</td>
</tr>
<tr>
<td>Duration of recording (hrs)</td>
<td>55</td>
<td>Adjustable</td>
<td>50</td>
</tr>
<tr>
<td>Video format</td>
<td>.mp4</td>
<td>.mp4</td>
<td>.mp4</td>
</tr>
<tr>
<td>Display (inch)</td>
<td>5.5</td>
<td>6.5</td>
<td>Connectable to smart phone</td>
</tr>
<tr>
<td>Battery life (hrs)</td>
<td>72</td>
<td>48</td>
<td>50</td>
</tr>
<tr>
<td>Waterproof</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Operation temperature (°F)</td>
<td>-40 to 140</td>
<td></td>
<td>Withstands summer heat and winter cold</td>
</tr>
<tr>
<td>Installation time (minutes)</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

### Office preparation

At the office, a proper plan of fieldwork was conducted, which included preparing a checklist, scheduling of the fieldwork for each site, and work distribution among the fieldworkers. A checklist defines the list of instruments that are required for conducting fieldwork. In a typical survey day, a properly prepared checklist ensures that all the essential instruments are loaded in the vehicle for fieldwork. In this project, the distance from the selected sites to the office varied significantly (1 to 50 miles). When the team reached a site and found that a survey instrument was missing, it was not possible to return to the office to fetch it because there was insufficient time to do so. So, a checklist, as shown in table 3.2, was prepared for the site survey to avoid this kind of situation. On each survey day, all the survey instruments were loaded into the vehicle according to the checklist.
Table 3.2. Checklist for Fieldwork

<table>
<thead>
<tr>
<th>Instrument Name</th>
<th>Number required</th>
<th>Check</th>
</tr>
</thead>
<tbody>
<tr>
<td>Camera</td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td>Fully charged battery</td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>Traffic boxes</td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td>Plastic pole</td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>Steel pole</td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td>Steel angle</td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>Metal straps</td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td>Wheel measurer</td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>Hammer</td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td>Drill machine</td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>Safety vast</td>
<td></td>
<td>yes</td>
</tr>
</tbody>
</table>

The schedule of fieldwork defines a time plan for sites, which includes the survey day and departure time of a survey team from the office for each site. For a typical survey day, the number of sites for surveying was selected based on the required number of instruments and the distance of sites from the office. A single site was selected for a survey day when the site required the installation of all the available instruments because the site had numerous entrances and exits. Similarly, a group of sites was selected for a survey day when the available instruments were sufficient to cover multiple sites that had few entrances and exits. Selecting a group of sites for a survey day took into account the distance among the sites as well as the distance from the sites to the office because short distances helped the survey team install instruments before 8 AM. The departing time from the office was selected based on the distances of sites from the office and the number of sites served.

Work distribution is the assignment of survey work among the team members. Assignment of duties to individual workers in advance ensures smooth and efficient execution of the fieldwork. In this project, before each survey day, work was distributed among the team members. A team member was assigned to charging camera batteries and checking the availability of instruments.
before the survey day. On the survey day, the same person was responsible for handling the
checklist. He ensured that all the required instruments were loaded on the vehicle according to the
checklist. During the survey, the fieldwork was assigned to different team members. For example,
some members were responsible for finding suitable spots for the camera installation, and some
were responsible for installing and retrieving the cameras. After the survey, an individual was
responsible for downloading video data from the cameras and uploading them to the server.

**Execution of fieldwork**

The fieldwork was conducted according to the survey plan prepared at the office. On a
survey day, the first task of the survey team was to load the instruments in the vehicle according
to the checklist. From the experimental survey of this project, it was found that it takes about 30
minutes to load the instruments in the vehicle. So, the team had to come to the office 30 minutes
prior to the scheduled departing time. When the team reached a survey site, the first task was to
find suitable spots for the installation of the cameras. For selecting spots, the team preferred an
existing pole, i.e., electricity or telephone pole, because the existing pole gives better support to
the camera. When there was no existing pole, steel angles were used to support a 2-inch diameter
camera pole. Two steel angles were driven into the ground to provide support on either side of the
camera pole and were then secured with clamps. The average mounting height of the cameras was
10 feet because it was tested and found that this height generally prevents a vehicle in a closer lane
obscuring the view of a vehicle in the farther lane.

A few factors were checked during the camera installation. Firstly, the charge level of the
camera batteries was checked for the availability of sufficient charge. Secondly, the clarity of the
camera lenses was checked to ensure a clear video recording. Thirdly, a real-time clock (for
example, a smartphone clock) was shown in front of each video camera so that it could record the
time. The purpose of this task was to find the difference between the camera clock and the real-time clock. This time difference was adjusted when manual and automated counting were conducted. Fourthly, the installation angle of the camera was checked so that the camera covered a full view of the entrance or exit. An attempt was made to avoid including a view of adjacent roads as much as possible because vehicle movement on those roads confuses the manual and automated counting process. A typical view of camera footage is shown in figure 3.2. This figure shows that the main focus of the camera is the entrance. The camera display includes the recording date and a clock.

![Figure 3.2. Typical View of a Camera Display Including a Clock](image)

The retrieval of the cameras was conducted after 6 pm on the day following installation. While retrieving the cameras, it was checked whether the cameras had successfully saved all the video data. A check was conducted to ensure that all the instruments were retrieved and loaded in the vehicle.

When the survey team reached the office, video data from the retrieved cameras were downloaded on the computer and then uploaded on the server. After that, the batteries of all the
cameras were left for overnight charging. In addition, a check was performed for the availability of instruments for the next day survey.

**Data storage**

Accessibility, the capacity of storage, and safety were considered for selecting data storage. In this study, a considerable volume of video data was collected from the survey, and multiple individuals were involved in manual counting. So, it was considered necessary that multiple individuals could get access to the server simultaneously to conduct manual counting. At the same time, it was necessary that the server store the data safely. Thus, the server in the Intelligent Transportation System (ITS) Lab at the Louisiana Transportation Research Center (LTRC) was used for storing the data. The server is secured, has a large capacity, and accessible by multiple people at the same time. However, after downloading the video data from the cameras to the server, a copy of the data was also stored on an external hard drive to be on the safe side.

**Counting vehicles**

In this research, a few rules were followed for conducting the manual count. At first, the time interval of the count was selected. It was decided to count vehicles in 5-minute intervals because it allows counts to be aggregated in any multiple of 5 minutes. Then, the rule for counting arriving and departing vehicles were fixed by deciding that as soon as the front of a vehicle passed a reference line on the access road, it was counted as an arrival or departure. The numbers of arriving and departing vehicles were counted separately for each entrance or exit. After that, the number of vehicle classes for separate counting was selected. Vehicles were classified into six classes, which are Car, Motorcycle, Cycle, Pedestrian, Transit, and Others. A spreadsheet template, as shown in table 3.3, was used to record all manual counting results.
Table 3.3. Sample Manual Counts Sheet

<table>
<thead>
<tr>
<th>Time Start (hr:min:sec)</th>
<th>Time End (hr:min:sec)</th>
<th>Entry Details</th>
<th>Exit Details</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Counts in every 5 min interval</td>
<td>Counts in every 5 min interval</td>
</tr>
<tr>
<td>Car</td>
<td>Motorcycle</td>
<td>Cycle</td>
<td>Pedestrian</td>
</tr>
<tr>
<td>8:00:00</td>
<td>8:04:59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:05:00</td>
<td>8:09:59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:10:00</td>
<td>8:14:59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8:15:00</td>
<td>8:19:59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--</td>
<td>--</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17:55:00</td>
<td>17:59:59</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Estimation of error

Different types of error can occur while conducting manual counts. These can be classified into three classes: total count error, classification error, and interval error. Strictly speaking, ground truth counts are not known, but repeated counting at a particular site was considered to produce ground truth counts for that site in this study. Thus, the first count was compared with the repeated counts to estimate errors. In this research, a few sites were randomly selected for conducting repeated counts.

**Total count error:** For a particular time interval, total count error is defined as the difference between the number of counted vehicles and the actual number of vehicles. The errors of individual time intervals can be summed and averaged to get a total count error. A common statistic of this type is the root mean square error (RMSE), or the percent root mean square error (%RMSE). It expresses the average error between estimated and observed values. The percent root mean square error (%RMSE) of total count from all sites over all time intervals can be estimated from the following formula:
\[ %RMSE = \sqrt{\frac{\sum_{i,k} (N_{a,k,i} - N_{c,k,i})^2}{N_{a,k,i}}} \times 100 \]  

(i)

Where,

\( i = \) a time interval;
\( I = \) total number of time intervals at site \( k; \)
\( k = \) a site;
\( K = \) total number of sites;
\( N_{a,k,i} = \) actual count of vehicles at site \( k \) in time interval \( i; \) and
\( N_{c,k,i} = \) counted vehicles at site \( k \) in time interval \( i.\)

**Classification error:** The classification error defines the difference between the actual classified counts and the counted vehicles for a particular vehicle class. A classification error occurs due to the placement of a count in a different vehicle class. It is assumed that classification error increases with the increase of vehicle classes because more vehicle classes require more subdivisions in counts. The following formula can be used to estimate the percent RMSE of classification counts.

\[ %RMSE = \sqrt{\frac{\sum_{i,k} \left( \frac{\sum_{v} (N_{a,k,i,v} - N_{c,k,i,v})}{N_{a,k,i}} \right)^2}{I \times K}} \times 100 \]  

(ii)

Where,

\( i = \) a time interval;
\( I = \) total number of time intervals at site \( k; \)
\( k = \) a site;
\( K = \) total number of sites;
\( v = \) a vehicle class;
V = total vehicle classes;

\( N_{a,k,i,v} \) = actual count of vehicles at site k in time interval i for vehicle class v;

\( N_{c,k,i,v} \) = counted vehicles at site k in time interval i for vehicle class v; and

\( N_{a,k,i} \) = actual count of vehicles at site k in time interval i.

**Interval error:** Interval error occurs when a count is placed into a different time interval than the one to which it belongs. So, for a single time interval, for example, 5 minutes, it can be defined as the difference between the actual count of vehicles and the counted vehicles. Then the errors for all time intervals are summed to get the total interval count error. Formula (iii) can be used to calculate the percent RMSE of interval counts.

\[
%RMSE = \sqrt{\frac{\sum_{i=1}^{I} \sum_{k=1}^{K} \left( \frac{n_{i,k}}{N_{a,k,i}} \right)^2}{I \times K}} \times 100
\]

Where,

i = a time interval;

I = total number of time intervals at site k;

k = a site;

K = total number of sites;

n = the number of misreported vehicles at site k at time interval i, which actually belongs; to a time interval (i+1); and

\( N_{a,k,i} \) = actual count of vehicles at site k in time interval i.

### 3.2. Automated Counting

**Develop algorithms**

Three deep learning object detectors were considered in this study: 1. R-CNN (Regional Convolutional Neural Network) and its variants, including the original R-CNN, Fast R- CNN, and Faster R-CNN, 2. SSD (Single Shot Detector) and 3. YOLO (You Only Look Once). The
performance of YOLO was found to be superior to other neural network-based object detectors in terms of accuracy and speed. However, when the target image (i.e., the video frame) contains small objects, the accuracy of the YOLO model is reduced, which is the only major limitation of the model. Fortunately, vehicle and pedestrian counts do not constitute tiny objects in the images in this project, so the YOLO object detector was selected for vehicle counting in this study. So far, YOLO comes in three versions: YOLOv1, YOLOv2, and YOLOv3. The latest version of YOLO, i.e., YOLOv3, is fast, accurate, and easier to work with than the other versions. Thus, YOLOv3 was applied with the TensorFlow and Open CV libraries for vehicle detection and counting. Python was used for developing all the algorithms.

In this study, vehicle counting is conducted in three steps: detection, tracking, and counting vehicles. First, a YOLO pre-trained object detection model was borrowed from the literature to detect vehicles in each frame, but programs were developed to implement YOLO in Tensorflow, such as loading the YOLO weight file to the program, calling YOLO to detect an object, editing the threshold value of the non-maximal suppression method of YOLO and so on. In addition, the YOLO weight file was converted to TensorFlow API. In this step, programs were developed to show the first frame of a video file, allowing users to select two random points on the first frame and drawing three reference lines. Second, programs were developed to implement Tensorflow to track vehicles from frame to frame. Also, programs were developed to draw bounding boxes around objects detected by YOLO and a centerline as well. Third, algorithms were developed to implement the logic of directional vehicle counts and counts in a flexible time interval. Moreover, programs were developed to transmit counts to an Excel sheet.

**Conversion of YOLO weight file to TensorFlow API:** The algorithms of the YOLO weight file are written in C/C++. In this study, the YOLO weight file was converted to TensorFlow
architecture in order to apply the file using Python programming. The required packages for this conversion were TensorFlow 18.0, Numpy, OpenCV Python, and TQDM. TensorFlow is a deep learning library used for different applications, such as neural network applications. NumPy is a package of routines in Python which support many mathematical functions on multidimensional arrays. OpenCV (open-source computer vision library) is an open-source library used in computer vision applications. TQDM is a progress bar library which provides useful routines for nested loops. The YOLO weight file was downloaded from the official YOLO website (pjreddie.com), which is open source. Then, the path of the downloaded YOLO weight file was placed under the root project directory ‘./data/darknet_weights/’ in the command prompt. The ‘python convert_weight.py’ command was run from the project directory, which converted the YOLO weight file to the TensorFlow format. This converted weight file was later used for vehicle detection.

**Settings for input files:** This section deals with defining a few essential arguments which were developed in this project. The essential arguments are model_path (path of the YOLO weight file), anchors_path (path of the anchor definitions), classes_path (path of the YOLO model class definition), and gpu_num (path of the number of graphics procession units available for use). The arguments for the input video file were also developed, the main inputs of which are the name of the video file and the video file path. The ‘parser’ task was used to define these arguments. All these arguments were executed by the function '__main__', which is the starting function of the whole program that managed the vehicle detection algorithms.

All video files need to be processed before uploading them to the program. First, it is checked that all the video files are in the mp4 format; otherwise, they are converted to the mp4 format. Second, if there are multiple video files, they are joined to make a single video file because
the program cannot process multiple files at a time. Third, the unnecessary portions of the video files, i.e., the portions before 8 am and after 6 pm, are trimmed. This pre-processing of video files can be conducted using any video editing software. In this research, the ‘Avidemux’ (a free video editing software) was used for processing video files.

When conducting automated counting, the video file is uploaded in the section titled 'input.' This task is performed by dragging and dropping the video file in the input section. The name of the video file is manually written in the “.mp4” title. When the program is run, it checks for all the configurations (i.e., model path, classes, etc.) in the defined arguments. After that, the program looks for the inputs of the video file. If it gets the video file name and the video file path, it moves to the processing step.

Detection of vehicles: In this section, programs were developed to draw reference lines and detect vehicles in each frame. The programs allow users to draw reference lines in the first frame of a video file. For the detection of objects in each frame converted YOLO weight file was used, but a few programs were developed to execute the detection process, such as the conversion of each image to a common size and providing threshold value to sort out potential detected objects. When the input argument gets the name and the path of an input video file, the program calls the 'detect_start' function and passes the video file name and path. This function calls the function 'getFirstFrame' to capture the first frame of the video. Then the program calls the 'get_points' function and shows the first frame on the computer display. OpenCV captures and displays the first frame of the video file. A typical first frame of this study is shown in figure 3.3.

Next, the program calls the 'setMouseCallback' function, which was developed in this study. The arguments of this function are mainly the first frame of a video file and the function titled 'mouse_handler.' The 'mouse_handler' function allows the user to select two points on the
displayed first frame, which are the starting and ending point of a reference line. These two points are drawn by the first and second left click of the mouse. Then, the program calls the 'detect_video' function, which connects the selected two points and draws the reference line.

![Image](image)

**Figure 3.3. The First Frame of a Video**

After that, the program opens the video file and shows the reference line. The reference line drawn in this section is called the 'mid_line.' A typical reference mid line is shown as the yellow line in figure 3.4. Afterward, the 'while True' (a conditional loop statement) is executed to open every frame of the video file.

![Image](image)

**Figure 3.4. Reference Lines Drawn in the Program Interface**
The program then calls the 'detect_image' function. The parameters of this function are a single frame of the video and the reference line (midline). Under this function, a few more functions are defined such as 'get_right_line' and 'get_left_line'. The 'get_right_line' function draws a parallel on the right side of the 'mid_line.' Similarly, the 'get_left_line' draws another parallel line on the left side of the 'mid_line.' Normal geometry-based arguments are applied to draw these parallel lines. There are no input points for drawing these parallel lines. When the program draws the mid reference line, it also draws the parallel reference lines.

The 'detect_image' function passes each video frame to the function 'letter_box image'. This function converts each video frame to a common size because the converted YOLO weight file in the TensorFlow API requires a common size of each frame to process the video. In this study, 128 x 128 pixels are used for the conversion of the video file. Then, TensorFlow calls the converted YOLO weight file to detect objects (i.e., vehicles) in each frame. At this stage, the YOLO weight file detects every potential object in an image. When YOLO detects an object, it draws a rectangular box around the detected object. The outputs of a processed image are rectangular bounding boxes and the score of those boxes. The score means a confidence level for a detected object, i.e., how confident YOLO is that the box contains a valid object. This value lies in the range of 0 to 1. The higher the score value, the higher the confidence that an object is indeed an object of interest. In this study, algorithms were developed for the conversion of each video frame to a common size and implementation of YOLO on the Tensorflow platform.

The bounding boxes are processed using a non-maximal suppression method in YOLO. The controlling factor in this process is a threshold value (a factor to screen out bounding boxes with low confidence levels). In this research, a threshold value of 0.2 was used, which means that bounding boxes having a score value higher than 0.2 are accepted for further processing. Those
that have values below 0.2 are eliminated. The sorted bounding boxes are sent to the 'dets' array to track detected vehicles. In this section, a few programs were developed to provide the threshold value to the YOLO weight file.

**Tracking Vehicles:** In this step, the sorted bounding boxes are tracked frame by frame. For the tracking process, KalmanBoxTracker was used. In this research, programs were developed to draw a centerline on each bounding box. Since a video file consists of thousands of frames, an object must be tracked from one frame to another to determine its direction of movement. The 'dets' array refers to the sorted bounding boxes to the 'update' function. This function calls the 'KalmanBoxTracker' to track vehicles from frame to frame. This tracker compares the current frame with the immediately previous frame using the pixel variance of the frame. When it finds a similarity in pixel values, it updates the object (i.e., bounding box) and memorizes it for consideration in the next frame. Then, it compares the updated frame to the next frame. The tracker titles each tracked bounding box by a numeric value such as 1, 2, 3, etc. In this way, the tracker tracks an object from frame to frame.

Rectangles are drawn around each tracked object on the computer screen, as shown in figure 3.5. This task is accomplished by the 'draw.rectangle.' function, which was developed in this study. Another purpose of drawing rectangle is to establish a small line in the center of each rectangle, which is used to count vehicles as described in greater detail in the “algorithm for counting” below. The function 'draw.line' draws a centerline of the rectangles. A typical centerline is shown in figure 3.4 as marked by the red color arrow. The tracked rectangles are observed for vehicle counting.
**Settings for Output File:** The program provides counts in the spreadsheet, which contains the number of arriving and departing vehicles in a particular time interval. All the programs for the output files were developed in this research. The counting speed of YOLO is different from the real-time clock. But this research requires to count vehicles in a time interval in real-time. So, at first, the program evaluates the number of frames in the provided time interval. After that, the program calculates the time required to process a single frame. Then, it evaluates the processing time of the video for the time interval and considers that time as an interval. The conversion is performed using the ‘write_to_excel’ function. There are three inputs in this function, which are a time interval, entry direction, and exit direction of vehicles.

**Algorithm for counting Vehicles:** When a vehicle passes through an access road to a facility, the rectangles and the small line at the center of the rectangle (i.e., the center-line) pass the mid-line and left and right lines parallel to it. Depending on the sequence of the intersection of the ‘center-line’ with the ‘mid line’ and the left and right lines, the direction of the vehicle is recorded. Programs were developed to count vehicles. For example, when the centerline at the center of the rectangle intersects the left line first (i.e., the parallel line, drawn on the left side of the ‘mid line’), the program deduces the vehicle has come from the left side. Afterward, when it
insects the 'mid line', the program confirms that the vehicle has come from the left side and consider it as a count. The 'leftToRight_counter' and 'rightToLeft_counter' functions count the vehicles which come from the left side and right side, respectively, and are used to distinguish arrivals and departures. The counts are shown on the computer display by the function 'cv2.putText'. The program can only conduct directional vehicle counts; it cannot classify the vehicles, i.e., bus, trucks, bikes and so on.

**Apply YOLO with OpenCV and CUDA:** Before running the program, YOLO must be applied with OpenCV (Open Source Computer Vision Library) to allow YOLO to operate in a GPU environment at increased video processing speed. To accomplish this, two open-source programs, cuDNN (a deep neural network-based library that provides graphics processing unit functionality), and CUDA (NVIDIA's programming language to the code graphics card), are required. Both cuDNN and CUDA can be downloaded from the NVIDIA website (developer.nvidia.com). CUDA must be installed properly since the success of the application of YOLO with OpenCV and cuDNN depends on the correct installation of CUDA. The success of the installation can be checked by running a sample video file in the program. If the installation is successful, the graphics properties are shown at the bottom of the program as response to the installation.

**Embedded hardware platforms**

In this study, the platform on which the program was run is as follows:

**Processor:** Intel(R) Core(TM)i7-8750CPU @ 2.20 GHz 2.21 GHz

**RAM:** 2.7 GHz, 16.0 GB

**GPU:** NVIDIA GeForce GTX 1060, 6GB
On this platform, it was found that an hour video takes 1.4 to 1.5 hours to process. It is recommended to use a high configuration computer for processing videos. A GPU of 2060 with a video memory of more than 6 GB is recommended for timely processing.

**Benefit-cost analysis**

Field data collection is the same for manual and automated counts, but traffic counting (i.e., the processing of the data) is different. In manual counts, traffic counts are conducted by trained individuals. In automated counting, traffic counts are performed by a computer. A benefit-cost (B/C) analysis is described below to compare the traditional (manual count) and automated methods.

The actual benefit of conducting a traffic count survey is unknown, but it is the same for both methods. Since surveys are conducted, it is recognized that their benefit must at least equal or exceed the cost of conducting the survey. Thus, the hours are taken to conduct video data collection, and manual counts were converted to monetary value and assumed to be the minimum benefit of the survey. For video data collection, working hours taken to conduct fieldwork was estimated and then converted to a monetary value using the payment rate of 10 dollars per hour. To estimate the cost of conducting manual counts, the time taken to process videos at each site was estimated. In this research, it was found that it took 21 minutes to manually count an hour of a video file. This proportion was used to estimate the actual hours taken to count videos from all sites. The total counting time was converted to a monetary value applying a payment rate of 10 dollars per hour.

The cost is different for the two methods. For the traditional method, the cost calculation is similar to the benefit calculation. For the automated method, the cost was calculated in a different way. Although automated counting is conducted by computer algorithms using a hardware
platform, an individual is appointed to upload video data to the computer program to conduct counts. The individual is paid for the hours taken to upload videos in the program. Also, before uploading videos, the individual has to conduct some processing of videos, such as converting all videos to mp4 format and joining videos. After uploading videos to the program, the computer is left for hours to process videos. From this research experience, it was found that it takes 15 minutes to process and upload 10 hours of videos to the program. This factor was applied to convert video hours to working hours. After that, the hourly pay rate was used to estimate the cost of automated counting. This cost was added to the cost of collecting field data to estimate the cost of the automated method.

The following formula was used to estimate the benefit-cost ratio (B/C) ratio for the traditional method.

\[
\frac{B}{C} = \frac{\text{Benefit}}{\text{Cost}} = \frac{\geq \left( \sum_{k=1}^{K} \text{time for field data collection (hrs)} + \sum_{k=1}^{K} \text{time for conducting manual counts (hrs)} \right)}{\sum_{k=1}^{K} \text{time for field data collection (hrs)} + \sum_{k=1}^{K} \text{time for conducting manual counts (hrs)}}
\]

\[
\approx \frac{\geq \left( \sum_{k=1}^{K} \text{costs of field data collection (dollars)} + \sum_{k=1}^{K} \text{costs of conducting manual counts (dollars)} \right)}{\sum_{k=1}^{K} \text{costs of field data collection (dollars)} + \sum_{k=1}^{K} \text{costs of conducting manual counts (dollars)}}
\]

Where,

\( k = \) a site

\( K = \) total number of sites

In the case of the automated method, the following formula was used to estimate the benefit-cost (B/C) ratio.

\[
\frac{B}{C} = \frac{\text{Benefit}}{\text{Cost}} = \frac{\geq \left( \sum_{k=1}^{K} \text{time for field data collection (hrs)} + \sum_{k=1}^{K} \text{time for conducting automated counts (hrs)} \right)}{\sum_{k=1}^{K} \text{time for field data collection (hrs)} + \sum_{k=1}^{K} \text{time for conducting automated counts (hrs)}}
\]

\[
\approx \frac{\geq \left( \sum_{k=1}^{K} \text{costs of field data collection (dollars)} + \sum_{k=1}^{K} \text{costs of conducting manual counts (dollars)} \right)}{\sum_{k=1}^{K} \text{costs of field data collection (dollars)} + \sum_{k=1}^{K} \text{costs of conducting automated counts (dollars)}}
\]
Where,

\(k\) = a site

\(K\) = total number of sites
Chapter 4. Result and Analysis

4.1. Manual Counting

Determination of counting time

Conducting manual counts from pre-recorded videos in real-time is time-consuming. Using modern media players for manual counting is a suitable way to save time. Modern media players, for example, VLC media player, have the feature to increase the frames per second of a video file. This media player can increase the speed up to 16 times the average speed of a video. In this research, six individuals contributed to manual counts. Their reported time for an hour video count is shown in figure 4.1.

![Average time is 21 minutes](image)

Figure 4.1. Reported Hourly Manual Counting Time

From figure 4.1, it can be observed that the average counting time is 21 minutes. The individuals reported that it is difficult to conduct counts continuously for a long-time. After looking at the computer monitor at a particular point (i.e., reference line) for a long time, they lose concentration. So, they reported that after continuously counting for about one hour, they had to take a rest for a
few minutes. If this break is taken into consideration, then the average counting time is more than 21 minutes. The quality of videos also controls the time of manual counting. Low quality of videos results in more time for manual counting because individuals cannot increase the speed of videos. If they increase the speed of a low-quality video, they fail to recognize vehicles.

**Estimation of error in manual counts**

As mentioned in the Methodology chapter, there is no actual ground value to estimate errors of manual counts. But the errors can be estimated indirectly by conducting repeated counts and accepting them as actual counts. In this case, it is assumed that repeated counts are more accurate than the first counts. If the first repeated count is similar to the first count, it is considered that there is no significant error in the first count. On the other hand, if the repeated count is different from the first count, it is recommended to use the first repeated counts. In both cases, it is recommended to conduct a second repeated count to increase the confidence of counts by comparing second repeated counts with first repeated counts. Since repeated counts cost double time and money, it is necessary to limit repeated counting to only a few sites. In this study, the sites for repeated counting were selected randomly. The total, classification, and interval errors were estimated by comparing the first time counts with the repeated counts.

In this project, manual counting was conducted for 40 different sites. Out of those sites, five sites were randomly selected for repeated counting. The selected sites for repeated counting are shown in table 4.1. The first and repeated counts were conducted by different individuals.

**Table 4.1. Selected Sites for Manual Counting**

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6031 Siegen Ln, 70809</td>
</tr>
<tr>
<td>12</td>
<td>702 N Lobdell Hwy Suite 9, Port Allen, LA 70767</td>
</tr>
<tr>
<td>21</td>
<td>12240 Coursey Blvd, 70816</td>
</tr>
<tr>
<td>31</td>
<td>4404 Moss St, Lafayette, LA 70507</td>
</tr>
<tr>
<td>39</td>
<td>13091 Airline Hwy, Gonzales, LA 70737</td>
</tr>
</tbody>
</table>
**Total error:** First and repeated counts of daily entry, exit, and total vehicle counts at individual sites are shown in tables 4.2 and 4.3 for day-1 and day-2, respectively. The deviation of first counts from repeated counts was used to estimate total error. For each site, errors were estimated for entry, exit, and total counts of day-1 and day-2 individually. The estimations of errors are shown in table 4.2 and 4.3 for day-1 and day-2, respectively.

Table 4.2. Total Count Error for Day 1

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Entry</th>
<th></th>
<th>Exit</th>
<th></th>
<th>Total</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First</td>
<td>Repeated</td>
<td>Error (%)</td>
<td>First</td>
<td>Repeated</td>
<td>Error (%)</td>
</tr>
<tr>
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<td>306</td>
<td>309</td>
<td>1.00</td>
<td>289</td>
<td>287</td>
<td>-0.70</td>
</tr>
<tr>
<td>12</td>
<td>702 N Lobdell Hwy Suite 9,</td>
<td>405</td>
<td>410</td>
<td>1.30</td>
<td>384</td>
<td>387</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>Port Allen, LA 70767</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>21</td>
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<td>184</td>
<td>181</td>
<td>-1.70</td>
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<tr>
<td>31</td>
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<td>76</td>
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<td>68</td>
<td>1.50</td>
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<tr>
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<tr>
<td>39</td>
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<td>251</td>
<td>254</td>
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<td>232</td>
<td>0.90</td>
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<tr>
<td></td>
<td>Gonzales, LA 70737</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Table 4.3. Total Count Error for Day 2

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Entry</th>
<th></th>
<th>Exit</th>
<th></th>
<th>Total</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>First</td>
<td>Repeated</td>
<td>Error (%)</td>
<td>First</td>
<td>Repeated</td>
<td>Error (%)</td>
</tr>
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<td>1</td>
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<td>284</td>
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<td>259</td>
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</tr>
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<td></td>
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<td></td>
</tr>
<tr>
<td>21</td>
<td>12240 Coursey Blvd, 70816</td>
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<td>0.40</td>
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<tr>
<td>31</td>
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<td>59</td>
<td>59</td>
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<td>53</td>
<td>1.90</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Tables 4.2 and 4.3 show that most of the time, underestimation of counts occurs because individuals generally failed to report counts rather than overcount them. Overestimation of counts occurred in three cases, which are exit counts of site 1 for day 1, exit counts of site 21 for day 1, and entry counts of site 31 for day 1, as shown in table 4.2. The potential reported reasons for the
overestimation of counts are poor visibility, high speed of a vehicle, and overlapping of vehicles at the point of observation.

To get an overall estimate of the error in manual counting, the percent root mean square error (%RMSE) of the counts of tables 4.2 and 4.3 were calculated using formula (i) in the methodology section. The percent RMSE for day-1 and day-2 for all the sites 3 were found to be 0.65 percent and 0.96 percent, respectively. The estimated RMSE of total counts for day-1 and day-2 was found to be 0.82 percent.

Classification error: The classified first counts were compared with the classified repeated counts to estimate classification error. Classification errors of first, repeated, and total counts were estimated for day-1 and day-2 individually for each site. The classification error in vehicle number, repeated counts, and error in percent for day-1 and day-2 are shown in tables 4.4 and 4.5, respectively.

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Entry</th>
<th>Exit</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Error (No’s)</td>
<td>Repeated Counts</td>
<td>Error (%)</td>
</tr>
<tr>
<td>1</td>
<td>6031 Siegen Ln, 70809</td>
<td>3</td>
<td>309</td>
<td>1.00</td>
</tr>
<tr>
<td>12</td>
<td>702 N Lobdell Hwy Suite 9, Port Allen, LA 70767</td>
<td>3</td>
<td>410</td>
<td>0.80</td>
</tr>
<tr>
<td>21</td>
<td>12240 Coursey Blvd, 70816</td>
<td>2</td>
<td>224</td>
<td>0.90</td>
</tr>
<tr>
<td>31</td>
<td>4404 Moss St, Lafayette, LA 70507</td>
<td>1</td>
<td>75</td>
<td>1.40</td>
</tr>
<tr>
<td>39</td>
<td>13091 Airline Hwy, Gonzales, LA 70737</td>
<td>4</td>
<td>254</td>
<td>1.60</td>
</tr>
</tbody>
</table>
Table 4.5. Classification Error for Day 2

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Entry</th>
<th>Exit</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Error (%)</td>
<td>Repeated Counts</td>
<td>Error (%)</td>
</tr>
<tr>
<td>1</td>
<td>6031 Siegen Ln, 70809</td>
<td>0.70</td>
<td>288</td>
<td>1.10</td>
</tr>
<tr>
<td>12</td>
<td>702 N Lobdell Hwy Suite 9, Port Allen, LA 70767</td>
<td>1.90</td>
<td>487</td>
<td>1.30</td>
</tr>
<tr>
<td>21</td>
<td>12240 Coursey Blvd, 70816</td>
<td>1.30</td>
<td>247</td>
<td>1.00</td>
</tr>
<tr>
<td>31</td>
<td>4404 Moss St, Lafayette, LA 70507</td>
<td>0.00</td>
<td>59</td>
<td>2.00</td>
</tr>
<tr>
<td>39</td>
<td>13091 Airline Hwy, Gonzales, LA 70737</td>
<td>0.80</td>
<td>264</td>
<td>1.30</td>
</tr>
</tbody>
</table>

The percent RMSE of classification counts was calculated according to formula (ii) as mentioned in the methodology section. The estimated RMSE of day-1 and day-2 were found to be 1.02 percent and 1.18 percent, respectively. Total classification RMSE was found to be 1.10 percent.

**Interval error:** Interval error occurs when a vehicle count is recorded in an incorrect time interval. In this research, a 5-minute interval was considered for counting. The probability of an interval error increases as the interval time decreases, i.e., the probability of an interval error when using 5-minute intervals is higher than using 15-minute intervals. When interval time is decreased, counting is conducted in more subdivisions, which increases the probability of errors.

In this study, interval error was calculated by comparing the first counts with the repeated counts. Tables 4.6 and 4.7 show interval error in vehicle number, repeated counts, and error for day-1 and day-2, respectively. From the tables, it can be observed that the interval errors in percent are less than 2 percent, and in most of the cases, the errors are less than 1.50 percent.
Table 4.6. Interval Error for Day 1

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Entry</th>
<th>Exit</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Error (Nos)</td>
<td>Repeated Counts</td>
<td>Error (%)</td>
</tr>
<tr>
<td>1</td>
<td>6031 Siegen Ln, 70809</td>
<td>3</td>
<td>309</td>
<td>1.00</td>
</tr>
<tr>
<td>12</td>
<td>702 N Lobdell Hwy Suite 9, Port Allen, LA 70767</td>
<td>3</td>
<td>410</td>
<td>0.80</td>
</tr>
<tr>
<td>21</td>
<td>12240 Coursey Blvd, 70816</td>
<td>2</td>
<td>224</td>
<td>0.90</td>
</tr>
<tr>
<td>31</td>
<td>4404 Moss St, Lafayette, LA 70507</td>
<td>2</td>
<td>75</td>
<td>2.70</td>
</tr>
<tr>
<td>39</td>
<td>13091 Airline Hwy, Gonzales, LA 70737</td>
<td>4</td>
<td>254</td>
<td>1.60</td>
</tr>
</tbody>
</table>

Table 4.7. Interval Error for Day 2

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Entry</th>
<th>Exit</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Error (Nos)</td>
<td>Repeated Counts</td>
<td>Error (%)</td>
</tr>
<tr>
<td>1</td>
<td>6031 Siegen Ln, 70809</td>
<td>4</td>
<td>288</td>
<td>1.40</td>
</tr>
<tr>
<td>12</td>
<td>702 N Lobdell Hwy Suite 9, Port Allen, LA 70767</td>
<td>4</td>
<td>487</td>
<td>0.90</td>
</tr>
<tr>
<td>21</td>
<td>12240 Coursey Blvd, 70816</td>
<td>5</td>
<td>247</td>
<td>2.00</td>
</tr>
<tr>
<td>31</td>
<td>4404 Moss St, Lafayette, LA 70507</td>
<td>1</td>
<td>59</td>
<td>1.70</td>
</tr>
<tr>
<td>39</td>
<td>13091 Airline Hwy, Gonzales, LA 70737</td>
<td>3</td>
<td>264</td>
<td>1.20</td>
</tr>
</tbody>
</table>

Formula (iii), as shown in the methodology section, was used to estimate the percent RMSE of interval counts. RMSE of interval counts was found to be 1.23 percent and 1.40 percent, respectively. The total interval RMSE was found to be 1.31 percent.

**Analyzing error**

In the case of total error, it was observed that the underestimation of counts is the most frequent scenario because individuals generally fail to record counts. Overestimation of counts happens when a queue or a group of vehicles arrives or departs at high speed. Classification and interval errors do not have any effect on total counts. Interval error happens between the end and start of two adjacent intervals, so one interval error affects only the previous interval or the next
interval. Therefore, the interval error is not highly significant. Total and classification counts are generally used in practice. Total counts are usually used to calculate daily trips. Interval counts are used to estimating peak hour volume or expanded traffic counts. In this study, a few potential reasons for the errors were reported by the individuals who conducted manual counts. The reported errors are as follows:

- Due to a manual increase in frames per second in a media player, the chance of failure to recognize vehicles increases, is the main reason for total, classification, and interval error.
- It is hard to report vehicles for the videos which are recorded in the evening, heavy rain, or fog because, in these times, the quality of the video image is low.
- Raindrops obscure the camera lens, which makes a dark video frame, and individuals fail to report vehicles.
- Sometimes a queue of vehicles arrives and departs at the same time. In that case, the probability of error rises.

**General guidelines**

This section recommends general guidelines for the manual counting survey, which includes recommendations for site, time and instrument selection, planning, fieldwork, data storage, and conducting manual counts. The objective of this section is to provide guidance to a survey team so that they can conduct surveys successfully.

**Site selection:** The selection of sites is crucial because selected sites must represent the trips of an entire survey area. Generally, random sampling is used to identify sample sites. First, a sampling frame is selected from the survey area. Then, sites are randomly selected from the sampling frame.
**Time selection:** The selection of time depends on a few factors, which are the category of survey areas, season, and the characteristics of sites. The first factor that determines the selection of time is the category of a survey area. There are mainly three categories of sites: residential, industrial, or recreational. Typically, if an area is residential, then a survey can be conducted on any weekday because trip distribution is almost uniform on weekdays in residential areas. At weekends, residential areas generate mostly shopping and recreational trips. Thus, if peak period trips are needed, weekday, and weekend surveys in residential areas are appropriate. However, if the area is industrial, most trips are generated in the morning and afternoon peaks unless the industry is open at night. Recreational areas generate peak demand over weekends.

The characteristics of a site also control the survey time. A site may be characterized by the purpose of the site and the opening and closing hours of the business or complex. If a site is used for commercial purposes, the survey should be conducted on weekdays. If the survey site consists of residential buildings, both weekdays and weekends are recommended. The opening and closing hours of buildings determine the starting and ending time of a survey, respectively.

The season of a year for surveying varies depending on the category of the survey area. For residential and industrial areas, it is not suitable to survey in the summer because many people travel in the summer. In recreational areas, suitable times to survey are the summer, long weekends, and breaks because many people travel to these areas during this time.

**Camera selection:** The resolution, battery life, weight, and weather protection should be considered for the selection of the camera. The first factor to consider is the resolution of the camera. One of the errors that may occur while conducting a manual count is the failure to recognize vehicles. This kind of error happens due to low-quality video. Besides, low-quality video decreases the accuracy of automated counting. In this research, three makes of cameras were used,
two of them had 480p resolution, and the other one had 360p. The reason to choose a 360p camera was its availability, but later it had to be eliminated from the survey due to its poor resolution. The most common available resolutions for cameras are 360p, 480p, 720p and 1080p. From this research experience, it is recommended to use no lower than a 480p resolution camera.

The battery life and the charging time are important factors for long-duration video recording and repeated use of the camera. Obviously, the battery life should be longer than the duration of the site recording, but the question is, how much longer? Sometimes multiple sites are selected for a single survey day where the distances among the sites are significant. In this case, at the first site, cameras must be installed 1-2 hours ahead of regular installation time to complete installation in all sites before the starting time of recording. Moreover, due to the repeated use of batteries, battery life tends to decrease. Therefore, it is recommended to select cameras that have a minimum of 5 hours more battery life than the duration of a single site recording. Besides, the charging time of cameras should be considered. Sometimes cameras must be installed on the following day of retrieval. In this case, the available hours for charging batteries is 6 to 12 hours. So, the batteries of the cameras should be such that they can be fully charged within 6 hours.

The weight and handling factor of cameras should also be considered. In this study, it was found that one of the cameras was too heavy to install and retrieve by one person. So, it is recommended to select lightweight and easy handling cameras if one individual is involved in site installation and retrieval.

The ability of a camera to operate in bad weather is an important factor to consider. The survey area may have extreme weather, for example, too cold, too warm, heavy rain, or dense fog. The performance of the cameras should, ideally, continue during these weather conditions. Moreover, the cameras must be waterproof and weather resistant.
Another problem that may decrease the video quality is the clarity of the camera lens. Waterdrops result in an unclear video when it adheres to the camera lens. So, the camera lens should be such that the water does not adhere to the lens surface. In addition, before every installation, it must be verified that the camera lens is clear. It is recommended to use a relevant liquid cleaner (for example, liquid thinner) for cleaning the camera lens.

**Guidelines for fieldwork:** The guidelines of the manual counting survey are comprised of two parts: planning and execution. Planning is performed at the office and is a precursor to a successful survey. Execution is conducted based on former planning and includes the installation and retrieval of cameras.

**Planning:** The planning of a survey includes scheduling, preparing a checklist, and work distribution. The scheduling is the list of assigned survey days and departure time from the office for the sites. It must be completed before the execution of the survey. Scheduling depends on the inter and intra distance of sites, and the availability of instruments. The inter distance refers to the distance between the office and the site, and the intra distance is the distance between sites. If the inter distances of sites are long and intra distances are short, then a pair or a group of sites may be selected for a single survey day to save travel time and cost. In this case, adequate instruments must be available for site surveys.

The departing time refers to the time when the survey team departs from the office for the fieldwork. This time must be selected before the survey day. It is selected depending on the distances of the sites from the office and the number of survey sites. Since it may take time to find the camera installation points on the site, it is recommended to select the spots using Google maps at the office. These pre-defined spots can be printed and supplied to the team, which may accelerate the fieldwork.
A checklist is a list of all necessary instruments that are needed for typical fieldwork. This research recommends preparing a checklist to avoid instruments being unavailable when needed at the site. A team member must be assigned to ensure that all the required instruments are loaded on the vehicle according to the checklist. A typical checklist is shown in table 4.8.

Table 4.8. A Typical Checklist for Fieldwork

<table>
<thead>
<tr>
<th>Site Name:</th>
<th>Site address:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Date and time:</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Instrument Name</th>
<th>Number required (no’s)</th>
<th>Check</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>yes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>no</td>
</tr>
<tr>
<td>Camera</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fully charged battery</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Traffic boxes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Plastic pole</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel pole</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel angle</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metal straps</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wheel measurer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hammer</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drill</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safety vast</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel tape measure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Site map</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Survey plan</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Survey vehicle checking</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Permission form authority (if the survey site is private property)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Raincoat</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The fieldwork should be distributed among the team members ahead of a survey. For example, handling checklist, loading instruments into the vehicle, installing and retrieving cameras, downloading data, etc. should be assigned to individual team members. A few recommendations for a survey team are provided below from the experience of this survey project.
• Each team member must have detailed information on the site. For example, each member should be provided with a printed copy of the preselected camera installation spots, the departing time from the office, the location of sites and required instruments.

• Before the survey day, it must be determined whether the survey can be conducted entirely within the road reserve; otherwise, permission must be obtained from the landowner of sites.

• Since recording video in a public place or a commercial space is sensitive, it is recommended that team members must keep a personal identity card and a letter authorizing the survey in the event of an inquiry.

Execution: The survey team must come to the office ahead of the departing time to load the required instruments in the vehicle. This study recommends that the survey team should arrive at least 30 minutes ahead of departing time. Before departing from the office, a few checks must be conducted, which are as follows.

• Make sure camera batteries are fully charged.

• All the instruments are loaded into the vehicle according to the checklist.

• If possible, some spare batteries should be carried to the site.

When a team reaches a site, the first task is to find spots for camera installation. Then the team members should work according to their responsibility, i.e., unloading instruments, measuring distances, driving steel angles, and installing cameras. While installing cameras, the following factors should be addressed:

• Ensure the charge of batteries is sufficient to record through the survey day(s).

• Ensure the camera covers a full view of entrances or exits. While adjusting the focusing angle, adjacent roads should preferably not enter the field of view of the camera because
vehicles on those roads may confuse individuals while conducting counts. In addition, it also decreases the accuracy of automated counts.

- The display time of cameras must be checked. If the display time does match with the real clock, a clock (for example, a smartphone clock) can be shown to the camera so that it can record the real-time.
- It is recommended to use a 10 feet height for mounting cameras. But it can be adjusted if the installation spot is on a rough-slope.
- For supporting camera poles, steel angles can be used because they are easy to drive and retrieve.
- The lens of the camera must be checked for clarity.

The cameras must be retrieved at the planned time. The instruments should not be allowed to stay on the site unnecessarily. On the retrieving day, the following factors should be considered:

- It must be verified that the camera saved all the recordings successfully.
- It is recommended to switch off the cameras at the site.

When the team reaches the office, all instruments should be unloaded, and video data should be downloaded. After downloading video data, the data must be stored on a server. After that, the batteries should be recharged and all instruments prepared for the next survey. The following checks should be conducted at the office.

- Ensure camera memory is empty.
- Check that empty batteries are actively connected to the charger.

**Data storage:** Data storing is a sensitive task. The first factor for selecting storage is security. Since camera recordings may contain confidential data, the storage must not be accessible to other people. Moreover, business owners demand the confidentiality of the data because the
video footage may contain commercial information useful to their competition. Besides the confidentiality of the data, the security of the data itself against loss is of the utmost importance. Data must be stored in a safe and secure location. The second factor is accessibility. Since multiple individuals may be involved in counting, the stored data should always be accessible to them. The third factor is the capacity of the storage. The size of the storage must be large enough to store all the data. A copy of the data should also be stored on an independent external hard drive to stay on the safe side. However, this research recommends using a computer server for storing data because it is enormous and accessible by multiple people at the same time. Online storage, for example, Dropbox, is also a convenient means of storing data.

**Manual counts:** The format of manual counts depends on the requirements of a project. The first parameter of formatting is the time interval. This study recommends using a 5-minutes time interval so that the counts can be used to estimated peak-period count in any multiple of 5 minutes. The second parameter is the starting and ending time of counting. Generally, most of the businesses open at 8 AM and close at 6 PM. So, for a whole day survey, the starting time should not be after 8 AM, and the ending time should not be before 6 PM. For peak hour counting, the starting time and ending time can vary depending on the characteristics of a site such as land-use type, land use diversity, road density etc. Typically, peak hours at individual land uses occur within the period 4 PM to 6 PM. The third parameter is the vehicle classification. The number of vehicle classes depends on the requirements of a project. The counting time increases with an increase in vehicle classes, and it also increases the classification error. This investigation recommends classifying vehicles into as many classes as possible because it provides detailed data that can be aggregated later in a variety of ways. The fourth parameter is the number of lanes on the road. Counts may be reported according to the lanes so that the number of through, left-turning, and
right-turning vehicles can be separated. In general, the following practice is recommended for manual counting:

- It is recommended modern media players be used for manual counting because these players have the feature to increase the number of frames per second (fps), which reduces counting time. This research recommends using the VLC media player because it can increase the speed up to sixteen times. From this study, it was found that the average counting time for an hour video is 25 minutes.
- Before starting manual counting, it is recommended that completion time be estimated based on the available number of individuals and their speed of counting so that the project can be completed within the scheduled time.
- In this study, the individuals conducting manual counting reported they could not recognize vehicles when they counted continuously for a long time. So, it is recommended not to count continuously for more than an hour. A small break every hour is likely to decrease total, classification, and interval count errors.

4.2. Automated counting

Analyzing Video

In this section, the pre-recorded videos were analyzed by applying computer algorithms. The algorithms were used to automate the entry and exit counts of sites. Since computer processing of the video files took approximately 1.5 times the real-time, a sample of sites were randomly selected from the 40 sites to conduct automated counting.

The automated counting results from 10 randomly selected sites are shown in table 4.9.
Table 4.9. Automated Counting Data in Vehicles per Day

<table>
<thead>
<tr>
<th>Site No</th>
<th>Site Name</th>
<th>Day 1</th>
<th>Day 2</th>
<th>Day 1</th>
<th>Day 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Entry</td>
<td>Exit</td>
<td>Entry</td>
<td>Exit</td>
</tr>
<tr>
<td>1</td>
<td>6031 Siegen Ln, 70809</td>
<td>295</td>
<td>269</td>
<td>268</td>
<td>235</td>
</tr>
<tr>
<td>3</td>
<td>3148 Ambassador Caffery Pkwy</td>
<td>481</td>
<td>485</td>
<td>571</td>
<td>564</td>
</tr>
<tr>
<td>5</td>
<td>1712 SW Railroad Ave, Hammond, LA 70403</td>
<td>172</td>
<td>168</td>
<td>164</td>
<td>162</td>
</tr>
<tr>
<td>11</td>
<td>28811 Walker South Rd, Walker, LA 70785</td>
<td>154</td>
<td>145</td>
<td>182</td>
<td>181</td>
</tr>
<tr>
<td>15</td>
<td>5635 MAIN ST B, ZACHARY, LA 70791</td>
<td>335</td>
<td>331</td>
<td>281</td>
<td>264</td>
</tr>
<tr>
<td>18</td>
<td>1551 US-51 BUS, Ponchatoula, LA 70454</td>
<td>114</td>
<td>124</td>
<td>112</td>
<td>131</td>
</tr>
<tr>
<td>21</td>
<td>13711 Coursey Blvd</td>
<td>212</td>
<td>164</td>
<td>229</td>
<td>184</td>
</tr>
<tr>
<td>23</td>
<td>14210 Airline Hwy, 70737</td>
<td>162</td>
<td>145</td>
<td>121</td>
<td>112</td>
</tr>
<tr>
<td>28</td>
<td>13394 LA-73, Geismar, LA 70734</td>
<td>145</td>
<td>134</td>
<td>132</td>
<td>124</td>
</tr>
<tr>
<td>32</td>
<td>17134 Hwy 44, 70769</td>
<td>134</td>
<td>124</td>
<td>118</td>
<td>109</td>
</tr>
</tbody>
</table>

Accuracy Evaluation

Automated counts were compared with manual counts to estimate the accuracy of the automated counting. The accuracy of a daily entry, exit, and total counts of individual sites for day-1 and day-2 are shown in table 4.10 and 4.11, respectively.

Table 4.10. Accuracy of Automated Counting for Day 1

<table>
<thead>
<tr>
<th>Site No</th>
<th>Entry</th>
<th>Exit</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Manual</td>
<td>Automated</td>
<td>Accuracy (%)</td>
</tr>
<tr>
<td>1</td>
<td>309</td>
<td>295</td>
<td>95.47</td>
</tr>
<tr>
<td>3</td>
<td>526</td>
<td>481</td>
<td>91.44</td>
</tr>
<tr>
<td>5</td>
<td>196</td>
<td>172</td>
<td>87.76</td>
</tr>
<tr>
<td>11</td>
<td>172</td>
<td>154</td>
<td>89.53</td>
</tr>
<tr>
<td>15</td>
<td>354</td>
<td>335</td>
<td>94.63</td>
</tr>
<tr>
<td>18</td>
<td>149</td>
<td>114</td>
<td>76.51</td>
</tr>
<tr>
<td>21</td>
<td>224</td>
<td>212</td>
<td>94.64</td>
</tr>
<tr>
<td>23</td>
<td>180</td>
<td>162</td>
<td>90.00</td>
</tr>
<tr>
<td>28</td>
<td>162</td>
<td>145</td>
<td>89.51</td>
</tr>
<tr>
<td>32</td>
<td>159</td>
<td>134</td>
<td>84.28</td>
</tr>
</tbody>
</table>
Table 4.11. Accuracy of Automated Counting for Day 2

<table>
<thead>
<tr>
<th>Site No</th>
<th>Entry Manual</th>
<th>Entry Automated</th>
<th>Entry Accuracy (%)</th>
<th>Exit Manual</th>
<th>Exit Automated</th>
<th>Exit Accuracy (%)</th>
<th>Total Manual</th>
<th>Total Automated</th>
<th>Total Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>288</td>
<td>268</td>
<td>93.06</td>
<td>259</td>
<td>235</td>
<td>90.73</td>
<td>547</td>
<td>503</td>
<td>91.96</td>
</tr>
<tr>
<td>3</td>
<td>617</td>
<td>571</td>
<td>92.54</td>
<td>610</td>
<td>564</td>
<td>92.46</td>
<td>1227</td>
<td>1135</td>
<td>92.50</td>
</tr>
<tr>
<td>5</td>
<td>194</td>
<td>164</td>
<td>84.54</td>
<td>186</td>
<td>162</td>
<td>87.10</td>
<td>380</td>
<td>326</td>
<td>85.79</td>
</tr>
<tr>
<td>11</td>
<td>207</td>
<td>182</td>
<td>87.92</td>
<td>200</td>
<td>181</td>
<td>90.50</td>
<td>407</td>
<td>363</td>
<td>89.19</td>
</tr>
<tr>
<td>15</td>
<td>297</td>
<td>281</td>
<td>94.61</td>
<td>284</td>
<td>264</td>
<td>92.96</td>
<td>581</td>
<td>545</td>
<td>93.80</td>
</tr>
<tr>
<td>18</td>
<td>142</td>
<td>112</td>
<td>78.87</td>
<td>145</td>
<td>131</td>
<td>90.34</td>
<td>287</td>
<td>243</td>
<td>84.67</td>
</tr>
<tr>
<td>21</td>
<td>247</td>
<td>229</td>
<td>92.71</td>
<td>209</td>
<td>184</td>
<td>88.04</td>
<td>456</td>
<td>413</td>
<td>90.57</td>
</tr>
<tr>
<td>23</td>
<td>132</td>
<td>121</td>
<td>91.67</td>
<td>124</td>
<td>112</td>
<td>90.32</td>
<td>256</td>
<td>233</td>
<td>91.02</td>
</tr>
<tr>
<td>28</td>
<td>158</td>
<td>132</td>
<td>83.54</td>
<td>149</td>
<td>124</td>
<td>83.22</td>
<td>307</td>
<td>256</td>
<td>83.39</td>
</tr>
<tr>
<td>32</td>
<td>129</td>
<td>118</td>
<td>91.47</td>
<td>114</td>
<td>109</td>
<td>95.61</td>
<td>243</td>
<td>227</td>
<td>93.42</td>
</tr>
</tbody>
</table>

Manual counts were considered as the true data to calculate the accuracy of the automated counting. The minimum and maximum accuracy of entry and exit counts were found to be 76.51 percent and 95.66 percent, respectively. The minimum and maximum total accuracy of individual sites were found to be 78.81 percent and 95.14 percent, respectively. The estimated accuracy of all sites was 89.57 percent.

**Paired t-test:** A two-tailed paired t-test was performed to evaluate the similarity between manual and automated counts. When it is required to know the similarity between two variables of the same subject, a paired t-test is conducted. In this research, manual and automated counts were performed on 10 sites. So, manual and automated counts can be considered as two variables, and a site can be considered as the same subject of interest. It is required to know the difference in the observations of manual and automated counts, which can be greater, smaller, or equal to zero. So, a two-tailed paired t-test was selected to perform in this study.

A few assumptions were considered for this test. It was assumed that independent variables (i.e., sites) consist of two related groups (i.e., manual and automated counts), there are no significant outliers in the differences between manual and automated counts, and the
distribution of differences between manual and automated counts shows an approximate normal distribution.

The following hypotheses were considered:

\[ H_0: N_{ai} = N_{mi} \forall i \]
\[ H_A: N_{ai} \neq N_{mi} \forall i \]

where,

\[ N_{ai} = \text{automated total daily vehicle count at site } i \]
\[ N_{mi} = \text{manual total daily vehicle count at site } i \]

A paired t-test was conducted for two cases for day-1 and day-2 individually. In the first case, the t-test was conducted for the difference between manual and automated counts (i.e., manual – automated). In the second case, the test was conducted for the adjusted difference between manual and automated counts, where the adjustment was performed by the mean of the difference (i.e., manual – automated - mean). This second case was introduced to observe the effect of removing the undercounting bias in the results. The test results are shown in table 4.12, 4.13, 4.14, and 4.15.

Table 4.12. Paired T-Test Result for the Difference Between Manual and Automated Counts for Day 1

<p>| | |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Mean</td>
<td>44.10</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>18.91</td>
</tr>
<tr>
<td>Standard deviation of mean</td>
<td>5.98</td>
</tr>
<tr>
<td>T stat</td>
<td>7.37</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>30.12</td>
</tr>
</tbody>
</table>

Table 4.13. Paired T-Test for the Difference Between Manual and Automated Counts Adjusted by Mean (Manual-Automated-Mean) for Day 1

<p>| | |</p>
<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.60</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>18.91</td>
</tr>
<tr>
<td>Standard deviation of mean</td>
<td>5.98</td>
</tr>
<tr>
<td>T stat</td>
<td>-0.10</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>-14.57</td>
</tr>
</tbody>
</table>

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>44.70</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>20.38</td>
</tr>
<tr>
<td>Standard deviation of mean</td>
<td>6.44</td>
</tr>
<tr>
<td>T stat</td>
<td>6.93</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>30.12, 59.27</td>
</tr>
</tbody>
</table>

Table 4.15. Paired T-Test for the Difference Between Manual and Automated Counts Adjusted by Mean (Manual-Automated-Mean) for Day 2

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-2.84217E-15</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>20.38</td>
</tr>
<tr>
<td>Standard deviation of mean</td>
<td>6.44</td>
</tr>
<tr>
<td>T stat</td>
<td>-4.41008E-16</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>-14.57, 14.57</td>
</tr>
</tbody>
</table>

In the case of the difference between manual and automated counts, i.e., table 4.12 and table 4.14, the null hypothesis is rejected for both day-1 and day-2. So, it is found that manual and automated counts are significantly different. In the case of the adjusted difference between manual and automated counts, i.e., table 4.13 and table 4.15, the null hypothesis could not be rejected. So, it can be interpreted that manual and automated counts are not significantly different from each other if the consistent undercounting of the automated method is removed.

However, one of the assumptions of a two-tailed paired t-test is that data shows a normal distribution pattern. Since the sample size of the paired t-test is small, a normality test was conducted to see whether the sample shows a normal distribution. In this case, the difference between manual and automated counts for day-1 and day-2 were individually analyzed. From the test, it was found that the data for the difference between manual and automated counts for day-1 and day-2 does not show a normal distribution. The reason for not showing normal distribution is
random sampling and small data size. Therefore, it may be a potential reason for not showing the similarity of manual and automated counting data in the paired t-test.

**Confidence limits:** Confidence intervals were estimated for the difference between paired manual and automated counts for day-1 and day-2 individually. The results are shown in table 4.16 and 4.17 for day-1 and day-2, respectively.

Table 4. 16. Confidence Limits for the Difference Between Paired Observations for Day 1

<p>| | |</p>
<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>44.10</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>18.91</td>
</tr>
<tr>
<td>Sample size</td>
<td>10</td>
</tr>
<tr>
<td>Confidence coefficient (95%)</td>
<td>1.96</td>
</tr>
<tr>
<td>Margin of error</td>
<td>11.72</td>
</tr>
<tr>
<td>Upper confidence limit</td>
<td>55.82</td>
</tr>
<tr>
<td>Lower confidence limit</td>
<td>32.38</td>
</tr>
</tbody>
</table>

Table 4. 17 Confidence Limits for the Difference Between Paired Observations for Day 2

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>44.70</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>20.38</td>
</tr>
<tr>
<td>Sample size</td>
<td>10</td>
</tr>
<tr>
<td>Confidence coefficient (95%)</td>
<td>1.96</td>
</tr>
<tr>
<td>Margin of error</td>
<td>12.63</td>
</tr>
<tr>
<td>Upper confidence limit</td>
<td>57.33</td>
</tr>
<tr>
<td>Lower confidence limit</td>
<td>32.07</td>
</tr>
</tbody>
</table>

From table 4.16, it can be observed that the upper confidence limit is 55.82, and the lower limit is 32.38. So, it can be interpreted that there is a 95 percent chance that the true mean difference between paired observations will be in the range 55.82, 32.38, and there is a 5 percent chance that the true mean will not be in the range 55.82, 32.38.

Table 4.17 shows that the upper confidence limit is 57.33, and the lower limit is 32.07. From this confidence, it can be implied that there is a 95 percent chance that the true mean
difference between paired observations will be in the range 57.33, 32.07, and there is a 5 percent chance that the true mean will not be in the range 57.33, 32.07.

Potential reasons for the error

The potential reasons for error in automated counts are as follows.

- In the case of a parking lot, the arrival speed of a vehicle is generally higher than the departure speed. Figure 4.2 explains the scenario clearly. Here, vehicles leave the major road and take a right turn to enter the entrance of the parking lot, where they do not need to wait for any traffic signal or queue. But when vehicles depart from the parking lot, they have to wait for a gap in the major road, which causes a lower speed for departing vehicles. This program sometimes fails to count vehicles that have a high speed. The reason behind this is when vehicles arrive at high speed, the program does not get time to count because it appears in the frame for a too-short time. For this reason, the error for arriving vehicles is higher than for departing vehicles.

![Figure 4.2. Arrival and Depart Speed Comparison](image)

- The camera angle is a major reason for reducing the accuracy of counts. When the camera is close to the entrance, i.e., the vehicle appears large and covers most of the
frame, the program fails to count those vehicles. Moreover, when vehicles appear large, some parts of the vehicle are out of the frame, which makes it difficult for the program to detect the image as a vehicle. In figure 4.3, the camera is very close to the entrance, and it does not cover the whole view of the entrance. As a result, the UPS vehicle appears large and some parts of the vehicle are out of the frame. Although most of the time, the program can detect and count large vehicles, it is not the ideal view of the frame for automated counting.

![Figure 4.3. Unsuitable Camera Angle and View](image)

- Visibility is an important factor that controls the quality of the video. Low visibility results in poor video quality. Rain, low light, evening recording, and cloudy weather cause low visibility.
- Raindrops obscure the camera lenses and result in a bad quality of video recording. In this case, the program cannot count accurately.
- When two vehicles arrive and depart at a time, one vehicle overlaps another. In this case, the program cannot detect the overlapped vehicle and counts only one vehicle.
Analyzing accuracy

From the accuracy estimation of automated counts it can be observed that the programs undercount vehicles in the case of all sites. The reason behind this is the developed program always fails to detect vehicles but never overcounts vehicles. The failure to detect vehicles happens due to bad quality video footage.

The automated average accuracy of automated counting was found to be about 90 percent. The total number of entries and exits counts for day-1 and day-2 is 40. Out of those 40 cases, 26 cases show automated counts equal to or more than 90 percent, and the rest of the 14 sites shows accuracy less than 90 percent.

Benefit-cost analysis

The benefit-cost (B/C) analysis was conducted using the formulas as provided in the methodology section. The B/C calculation of the traditional method is as follows.

\[
\frac{B}{C} = \frac{\text{Benefit}}{\text{Cost}} = \frac{\geq (640 \text{ hrs} + 553 \text{ hrs})}{640 \text{ hrs} + 553 \text{ hrs}} \approx \frac{\geq (6400 + 5530)}{6400 + 5530} = (\geq 1)
\]

In the case of automated method, the B/C calculation is as follows.

\[
\frac{B}{C} = \frac{\text{Benefit}}{\text{Cost}} = \frac{\geq (640 \text{ hrs} + 553 \text{ hrs})}{640 \text{ hrs} + 39.5 \text{ hrs}} \approx \frac{\geq (6400 + 5530)}{6400 + 395} = (\geq 1.76)
\]

Comparison with other methods

Pneumatic road tube counting: Patrick McGowen and Micheal Sanderson (2011) conducted a study to evaluate the accuracy of the pneumatic road tube counter. According to their study, accuracy was found to be about 99 percent. The study also found that though the average error in a daily traffic count might be near zero, the absolute error of a typical 15-minute count averaged closer to 10%. These results suggest that the level of inaccuracy is being masked by the positive and negative counting errors canceling each other out. Errors in speed and classification
were much greater. These results raise questions about the reliability of pneumatic road tube counters in accurately measuring traffic volumes.

**Piezoelectric sensor:** When a vehicle passes over a piezoelectric sensor, mechanical energy passes to the sensor, and the sensor converts the mechanical energy to electrical energy. This electrical energy is analyzed for vehicle counting. This is a highly accurate method of traffic counting. The accuracy of traffic counts applying the piezoelectric sensor is reportedly 99 percent.

**Inductive loops:** According to Liao (2018), the loop signature system could obtain more accurate, reliable and comprehensive traffic performance measures for transportation agencies. He conducted several tests on inductive loops to find the accuracy of traffic counts. The study claims the accuracy of inductive loops to be 90 percent.

**Different computer algorithms:** Mattias Gustafsson and Sebastian Hjelm (2018) developed algorithms to conduct automated traffic counts from pre-recorded videos. They collected high-resolution video for automated traffic counts because high-resolution video increases the success of counts. They trained and evaluated several neural network models tasked with detecting and counting vehicles in various scenes and have achieved accuracies above 90%.

Pereira et al. (2016) also developed a computer algorithm for automated traffic counting and control. The goal of their study was to get counts in a faster and more economical way. They reported that the accuracy of their program varies from 60 percent to 70 percent. The study reported that low-resolution video is responsible for the failure of the program to count traffic.

The algorithms developed in this study are capable of providing 90 percent accurate counts which is equal or higher than the computer algorithms developed in other studies. Although the accuracy of Pneumatic Road tube counting, Piezoelectric Sensor, and Inductive loops is higher,
the cost of this technology is also high. Therefore, in terms of cost, developed computer algorithms are more feasible than conventional counting technologies.

**Recommendations**

The success of automated counting largely depends on the quality of the input video. Since the program analyzes each frame of the video, the quality of the video is an issue. So, the resolution of cameras must be good.

The second thing is the installation procedure for cameras. If the support of the camera poles is inadequate, for example, the steel angles supporting the camera pole are not driven deep enough, the camera can sway in the wind. From this research, it was observed that the accuracy of detecting objects decreases when the camera poles oscillate in this manner. Moreover, in windy weather, the height of the camera installation plays a role because the height leads to greater movement of the camera.

The angle of the cameras is an important factor that influences the quality of data. It has to ensure that the camera angle covers a wide view of entrances with a medium vehicle scale.

The third factor is the lenses of the cameras. The lenses should always be clear. Before installing cameras, it has to make sure that the camera lenses are clear.

**Limitations of the Program**

The counting speed of the program varies depending on the platform type. The counting speed increases with the configuration of the computer. Camera quality and camera installation play a critical role because, as mentioned above, if the image is not clear or if the camera moves or vibrates, the accuracy of observation is compromised. In addition, when two vehicles pass in the area of observation and one obscures the other, the program can detect only one vehicle.
Implementation of the Program

Although it takes 1 hour and 30 minutes to process a video applying the computer algorithms, in terms of accuracy, the program performs at a satisfactory level. The accuracy of the program was found to be about 90 percent. In addition, the program provides this accuracy level consistently except for video recording in low light, rain, fog, and vehicle overlapping. So, if it can make sure that the collected video data have good quality, then the program developed in this research can be applied directly to obtain traffic counts. This program can be applied for directional traffic counts and counts in a flexible time interval. Since the video processing speed is low, processed video data can be uploaded to the program, and the data processed overnight.

From the benefit-cost (B/C) analysis, the B/C was found to be greater than or equal 1 for traditional methods, which implies that the traditional method is profitable. In the automated method, the B/C ratio was found to be greater than or equal to 1.76, which reflects an improvement of profit by 76 percent. Therefore, it can be implied that in a project, the automated method is 76 percent more beneficial than the traditional method.
Chapter 5. Conclusion

This research fills the gap of general guidelines for manual counting surveys and presents a more accurate automated method of traffic counting from pre-recorded videos. The study provides general guidelines for a manual counting survey based on the experience gained during the survey. The experience of fieldwork implies that proper planning is required to obtain the desired success in automated counts. This study recommends following the guidelines as provided in the recommendation section for the selection of site, time of survey and instruments, preparing a checklist, office preparation, execution of fieldwork, and manual counts. In this study, the individuals reported that the average time taken to count an hour of a video manually is about 21 minutes. The average daily error in total, classification, and interval manual counts were found to be 0.70 percent, 1.04 percent, and 1.31 percent, respectively. From the benefit-cost (B/C) analysis, the B/C was found to be greater than or equal to 1 for the traditional method, and for the automated method, the ratio was found to be greater than or equal to 1.76. So, the automated method has an improvement of 76 benefits than the traditional method. Applying a pre-trained YOLO object detector in Tensorflow API, this study presents an efficient method of automated vehicle counts. The accuracy of automated counting was found to be about 90 % with automated counting consistently being undercounted. The average processing speed for an hour video was found to be about 1 hour and 30 minutes. The observations on raw video footage and automated counts reveals that camera angle, bad weather, and speed of approaching vehicles highly influence the accuracy of automated counting.
References


Horzyk, Adrian, and Efe Ergun. “YOLOv3 Precision Improvement by the Weighted Centers of Confidence Selection.” 2020 International Joint Conference on Neural Networks (IJCNN), 2020, doi:10.1109/ijcnn48605.2020.9206848.


Vita

Mishuk Majumder was born in Noakhali, Bangladesh. In November 2014, he graduated in Civil Engineering from the Khulna University of Engineering & Technology (KUET), Bangladesh. After graduation, he joined the industry where he worked as the design and supervision engineer in the Structural and Geotechnical engineering fields. After working a few years in the industry, he got motivated to pursue his higher study. In August 2018, he Enrolled in the Louisiana State University, Baton Rouge, in the Master’s program in the Department of Civil & Environmental Engineering. Currently, he is pursuing his Master’s degree and working as a Graduate Research Assistant for Dr. Chester G Wilmot. He was involved in several research projects related to traffic data collection and developing an automated vehicle counting method. Mishuk Majumder plans to receive his Master’s degree in this Fall semester, 2020, with a Transportation Engineering specialization.