DETECTOR DIAGNOSTICS, DATA CLEANING AND IMPROVED SINGLE LOOP VELOCITY ESTIMATION FROM CONVENTIONAL LOOP DETECTORS

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ABSTRACT

Loop detectors are the most common sensors employed by freeway traffic management agencies, which use the data in applications such as incident detection and traveler information. As dependence on traffic flow data increases, operating agencies have started adopting error-detection routines to evaluate the quality of the data, thus leading to meaningful traffic parameters. Most of these error-detection routines have been in the form of threshold value tests, which check aggregated data against minimum or maximum feasible values. There have been many efforts to improve the effectiveness of these error-detection routines by testing some combination of several parameters simultaneously. Some researchers followed a different approach by performing tests on individual vehicle actuations instead of aggregate data to identify problems in loop detectors and, hence, help in correcting them. This thesis builds off of this latter approach to develop detector validation tests, for both single as well as dual loops, with the idea of identifying the problems causing the errors in the data.

In addition to data quality, another important aspect that cannot be neglected is the accuracy of parameter estimation. Inefficiencies in estimating traffic parameters could degrade the performance from traffic monitoring applications that interpret the traffic data. For example, Single loops can measure only occupancy and flow, while velocity, often the most useful parameter, can only be estimated. Typically, velocities are estimated on the basis
of traffic flow, occupancy and assumed average vehicle lengths. This conventional approach is limited because of varying vehicle lengths. Many researchers have proposed alternatives to overcome this problem, but most of them require complex analysis to estimate velocities or cannot be implemented on location using the existing hardware. Though many of the methods work well under normal conditions, there has been limited research done to estimate reliable estimates under heavy truck traffic. This condition may arise as a function of location or time of day, e.g., proximity to a trucking facility or early mornings when the number of passenger vehicles drops. This thesis presents a new methodology to estimate velocities under such conditions. Finally, a methodology to estimate travel time patterns at a given location has been developed for off-line research purposes.

Key words:

Loop detectors; Single loop velocity; trucks; traffic surveillance; velocity estimation;
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CHAPTER 1

INTRODUCTION

Traffic congestion has become a major problem in many urban areas, forcing local transportation agencies to adopt traffic management strategies such as increasing the physical capacity of the transportation network by adding lanes or building new roads. But such physical expansions may not always be a viable or economical solution. The penetration of technology into transportation is another tool to combat congestion and has lead to Intelligent Transportation System (ITS) such as advanced traffic management systems and traveler information systems, ATMS and ATIS respectively. These tools can potentially increase network throughput, provide route guidance and traffic information to travelers, reduce the delay experienced by commuters, and the discomfort associated with travel in congested conditions. Real-time knowledge of the state of the transportation network is typically required for ATMS and ATIS, hence, accurate traffic data acquisition is essential for effective traffic surveillance, the backbone of such ITS applications.

Inductive loop detectors (ILDs) have been used for decades to collect traffic data in the United States and many other countries. Recent technological advances have lead to
other surveillance systems such as video image processors, laser radar detectors, microwave
detectors, passive infrared radars, magnetic detectors, ultrasonic detectors, and passive
acoustic detectors [1,2]. Most of these emerging technologies emulate the operation of ILDs
in the sense that a detection zone in each identifies the presence/absence of a vehicle. In
other words, all these detectors are point detectors, capable of measuring traffic conditions
at a location where they are installed. Each technology has its own advantages as well as
disadvantages. Regardless of the type of detector used, all of these systems are prone to
transient errors e.g., a vehicle changing lanes in the detection zone.

1.1 ILDs – Parameter estimation

ILDs can be deployed as single or double loops. A single loop records two transitions, i.e.,
the turn-on and turn-off times when a vehicle passes over it, thus providing flow, the
number of vehicles that pass a location per unit time, and occupancy, the percentage of a
given sample period a detector is occupied by vehicles.

Flow \( q_i \) in sample \( i \) is proportional to the count of all vehicles observed in that period.

\[
q_i = \frac{n_i}{T} \tag{1.1}
\]

\( n_i \) = number of vehicles that pass the detector during sample \( i \).

\( T \) = sampling period

Occupancy \( occ_i \) is the percentage of time the detector is occupied by vehicles in sample \( i \).

\[
occ_i = \frac{\sum_{k \in i} t_k}{T} \tag{1.2}
\]

\( t_k \) = vehicle \( k \)'s on-time.
Assuming vehicle lengths and velocities are not correlated, the mean velocity for sample \( i \) is normally calculated using the following equation:

\[
\hat{v}_i = \frac{\hat{L} \cdot q_i}{occ_i}
\]

(1.3)

\( \hat{v}_i \) = mean velocity of sample \( i \)

\( \hat{L} \) = assumed constant mean effective vehicle length

Coifman (2003) showed that by taking median velocity instead of mean velocity, the effect of long vehicles on velocity could be reduced.

\[
\bar{v}_i = \frac{\hat{L}}{\text{median on-time}_i}
\]

(1.4)

\( \text{median on-time}_i \) = median of all on-times seen in sample \( i \).

Unless otherwise specified, single loop velocity in this thesis refers to estimates from Equation 1.4. Individual vehicle velocity is estimated by using the following equation:

\[
\hat{v}_i = \frac{\hat{L}}{\text{moving median on-time}_i}
\]

(1.5)

A sample size of 11 vehicles is used for the moving median, centered on the current vehicle.

Vehicle length is simply the product of estimated velocity and on-time.

A double detector, sometimes called as a speed trap, consists of two single loops separated by a known distance and hence allows measuring speeds from the difference in a given vehicle’s arrival times at the two loops and the distance between the loops. Figure 1 shows the sequence of events that occur at a double loop detector when a vehicle passes over it [3], where,

on\(_1\) and on\(_2\) are called rising edges.
Figure 1.1: A vehicle passing over a double loop detector, (A) the two detection zones and vehicle trajectory in the time space plane (B) the associated turn-on and turn-off times at each detector. From [3].
off₁ and off₂ are called falling edges

\[ TT_r = \text{dual loop traversal time via rising edges} \]

\[ TT_f = \text{dual loop traversal time via falling edges} \]

\[ OT_1 = \text{total on-time at the first loop} \]

\[ OT_2 = \text{total on-time at the second loop} \]

Velocity is calculated by dividing the loop separation (20ft in the figure) with traversal time. Note that \( OT_1 \) and \( OT_2 \) include physical vehicle length and the length of the detection zone, or in other words, the product of velocity and on-time gives the sum of both lengths also called as effective vehicle length. Note that vehicle lengths in this thesis always refer to effective length, unless otherwise specified. To obtain the aggregate velocity for a sampling period of \( T \), the average (usually harmonic average) of individual vehicles’ velocities seen in that sample is taken.

It is clear from Figure 1.1 that two measurements are available for all the above-mentioned traffic measures, one from each loop. To compensate for accuracy limitations due to sampling frequency (the number of times a loop checks for the presence of a vehicle), the average of two measurements can be used. Thus, ILDs whether single or double, provide three fundamental traffic parameters – flow, velocity and occupancy.

Over the years, researchers have been successful in expanding the capabilities of point detectors by improving methodologies that estimate traffic data such as single loop velocity estimation [11-20] and truck flows [19] and developing new techniques that allow us to extract more information about the roadway. Some of those techniques include incident detection [21] and vehicle re-identification [22-23], which allow detecting the onset of congestion. Research continues in these areas to improve the accuracy and performance of
those techniques. Many of the techniques mentioned above rely on data intensive computer algorithms that analyze the latest traffic data. As these algorithms are data sensitive, it is important to ensure that the quality of data used is good and the estimation of traffic parameters is reasonably accurate.

1.2 Importance of Data Quality

Data quality is important for both real-time applications and for off-line applications that use archived data for research. In the latter case, traffic engineers and researchers require accurate data for understanding the actual behavior of traffic and improve the performance of applications. As dependence on traffic flow data increases, many operating agencies have started adopting error-detection routines, which typically look for infeasible values in aggregate flow, occupancy and velocity data. Though these routines help in identifying erroneous samples, it can leave gaps in the data and there is still debate over imputing those gaps with data interpreted from temporally adjacent samples [7]. Also, minor errors in the data may be overlooked by those routines as they simply check for plausible values against minimum or maximum thresholds. A better approach would be to identify the source of those errors and correct it [3, 8], rather than eliminating erroneous data after it is processed. The first part of this thesis focuses on data validation and follows the individual data approach to develop validation tests that help in identifying detector errors present in a dataset.

1.3 Importance of parameter estimation

Even if the data are good, improper estimation of traffic parameters can lead to poor results when interpreted. For example, it is well known that the estimated velocity from single loops
using Equation 1.3 is affected by the presence of long vehicles. Thus, when a longer vehicle passes a detector, we may erroneously estimate congested velocities in the middle of free flow. This phenomenon is more frequent during early morning, low flow conditions when the flow of passenger traffic decreases. So, caution should be adopted when interpreting transient non-free flow velocity estimates from single loops. Also, any metrics, such as travel time, estimated using poor velocity estimates are affected. Therefore, it is important to estimate the traffic parameters as accurately as possible. The second part of this thesis deals with the improvement of single loop velocity estimation and travel time for off-line research.

1.4 Overview of the thesis

The main objective of this thesis is to obtain improved single loop velocity estimates from the data. To this end, detector tests are developed to identify problems and data cleaning techniques are used to obtain more accurate velocity estimates. Finally, a methodology for travel time estimation is presented as an example application of the improved estimates to demonstrate the resulting impacts.

Chapter 2 of this thesis reviews the research done in the area of detector diagnostics and the drawbacks of existing methods of estimating single loop velocity under heavy truck traffic. It also gives an overview of the research done in the area of travel time estimation. Chapter 3 focuses on detector diagnostics and data cleaning. Chapter 4 discusses a hybrid method of estimating single loop velocity in the presence of heavy truck traffic. The second part of chapter 4 explains the proposed methodology to estimate travel time for offline research purposes and illustrates how it can improve by starting with cleaner velocity estimates. Chapter 5 concludes the thesis and identifies the scope of current work and the areas for future research.
CHAPTER 2

LITERATURE REVIEW

2.1 Detector data validation

To better manage the transportation network, it is often desired to monitor traffic conditions automatically. Loop detectors are the most common sensors used to obtain data, which are supplied as input to applications such as travel time prediction, ramp metering and incident detection. Feeding incorrect data into these applications can lead to poor results and a lack of data may be preferred to erroneous data. To ensure that data from a detector is meaningful error checking measures can be introduced at two levels. The first is at the controller level which collects the individual vehicle actuations (microscopic data or event data) and the second is at a central computer level which receives data from various controllers after aggregation to average flow, velocity and occupancy data (macroscopic data). Normally the error checking measures are in the form of threshold value tests, i.e., check if each of the observed traffic parameters falls within predetermined minimum or maximum bounds. For example, at the macroscopic level, if the vehicle counts observed in a sample period of $T$ seconds exceeds a user-defined upper limit, the data from that sample are considered erroneous. Similar tests are commonly performed on
occupancy and velocity data as well. Though these tests identify erroneous samples, the range of acceptable values for these tests is often very large. Often, it is implicit in these tests that the acceptable range for a given variable is independent of the values of the other variables, i.e., multiple variables are not tested. So occupancy of 4 percent corresponding to a flow of 2500 vehicles/hr, will escape the tests though we do not expect to see such combination. To identify such samples, tests that examine multiple variables related by traffic flow theory were developed by researchers, e.g., Jacobson et al [4] developed a combination test specifying a range of possible flow values for a given occupancy based on empirically observed relationship between flow and occupancy. Cleghorn et al [5] improved the screening by devising a method to obtain tighter bounds for the test used to identify feasible flow-occupancy pairs. In addition, they suggested comparing data between two loops of a paired loop. If the number of samples from paired loops that do not fall within a predetermined range selected based on traffic conditions (whether free flow or congested) is large, it indicates a loop pair in need of calibration. There are efforts by other researchers (Turochy and Smith [6], Chao Chen et al [7]) to further improve the error detection capabilities using macroscopic tests and improve algorithms that impute erroneous and missing data with new values to form a “clean” data set. But many of these imputing algorithms lack sufficient justification and research is ongoing in this area.

Chen and May [8] deviated from the macroscopic data approach and used microscopic data to assess the working of detectors. Average on-time from one detector is compared with the average on-time across all lanes at a detector station. But their methodology is sensitive to pulse breakups, where a single vehicle is detected multiple times. Also, they fail to account for the impacts of non-freeflow velocities. Coifman [9] also used event data from dual loop detectors to identify errors in detectors by comparing the on-
times between loops in a dual loop during free flow. If the difference between the on-times deviates significantly from zero, it indicates hardware or software problems. A threshold of 2/60 seconds was used in that study. Coifman and Dhoorjaty [3] developed detector validation tests that identified detector errors both at single and dual loop detectors. But the eight tests introduced in their paper may not capture some major problems, for example, changes in detector sensitivity, which affects on-time and hence single loop velocity estimation. This thesis expands the approach of Coifman and Dhoorjaty [3] by introducing new tests that can be applied to event data to identify detector errors. Chapter 3 discusses more about the tests and their implementation.

2.2 Single Loop Velocity Estimation

Equation 1.3 is commonly employed to estimate velocity at single loop detectors. Wang and Nihan [10] also demonstrated that \( L \) is not a constant and suggested that it should be updated periodically to reflect changing traffic compositions and thereby avoid obtaining biased estimates. Coifman [11] suggested that improved velocity estimates could be obtained if \( L \) is estimated from free flow periods in a day. Hellinga [12] exploited the fact that traffic surveillance systems contain both single as well as dual loops. When effective vehicle length estimated at a neighboring dual loop is used for a single loop, the resulting velocity estimates were less accurate than those obtained by using constant vehicle length. Performing volume weighted exponential smoothing and applying a speed correction factor improved the results, but this approach fails when there are no dual loops near a single loop. Coifman et al [13] has shown that taking median velocity, Equation 1.4, instead of mean velocity, Equation 1.3, can reduce the effect of long vehicles in a sample, as the median is less sensitive to outliers
than mean. The resulting velocity estimates improved significantly when the percentage of long vehicles was less than 15 percent of the passing traffic. Research presented in this thesis will show that this improvement can still yield significant errors in the presence of heavier truck flows.

Other researchers have sought more complicated models. Pushkar et al [14] developed a cusp catastrophe model to estimate velocity. Compared to the estimates from Equation 1.3, their methodology produced more reasonable velocities with less scatter. But it is not clear how easy it would be to generalize their technique to other locations. Dailey [15] developed a statistical algorithm to estimate velocities that considers individual vehicle speed and length to be random variables using a Kalman filter to estimate velocity, and it was observed that the estimates reflected the variability in velocity as a function of time with a smaller variance than the measured speed.

Other studies to estimate single loop velocities were based on vehicle classification techniques. Sun et al [16] used inductive waveforms of vehicles that are output from new detector sensors to extract vehicle lengths and thus obtain more accurate velocity estimates. The algorithm was found to be robust under different traffic conditions but the main disadvantage is that the inductive waveforms are not available from most detectors. Wang and Nihan [10] built a log-linear model to estimate mean effective length to classify vehicles with single loop data. More recently, Wang and Nihan [17-18] developed new algorithms for classifying vehicles, whose accuracy was comparable to that of a dual loop. None of the methods described has seen widespread deployment.

Chapter 3 of this thesis extends the approach of Coifman [13] by developing a hybrid methodology that includes the velocity estimates from Equation 1.4 and velocities of long vehicles found out using a new method developed in this research called the on-time ratio.
2.3 Travel time estimation

Travel time is one metric often used by planners and engineers to evaluate transportation facilities and plan improvements because it is a simple concept understood by a wide variety of people. Although many sophisticated hardware and software approaches have been developed over the years [22-33] sometimes a simpler approach is sufficient, namely, assuming that local conditions at the detector station apply to an extended link between stations. The travel time between two detector stations is the sum of time taken by a virtual vehicle to travel each link with velocity determined by the time and location of the vehicle. The idea is not new and has been used earlier, e.g., the Washington Department of Transportation uses a similar methodology to provide real-time travel time information [35]. The second part of chapter 4 discusses more about the above method and compares the estimated travel times after using the improved velocity estimation with GPS equipped, probe vehicle travel times.
As noted earlier, it is important to ensure that the data fed into traffic monitoring applications, such as incident detection, are reasonably free from errors so that traffic management decisions could be made with confidence. To prevent errors from affecting the performance and utility of such applications, an understanding of the nature of possible errors is required so that error-detection routines could be developed. These routines can sometimes identify the source of errors, and thus malfunctions in the detector hardware or software, if any, could be corrected. The following section discusses more about the detector errors. Although the following section focuses on errors from loop detectors, it is important to note that many vehicle detection technologies are prone to some kinds of errors similar to the ones discussed in the section, and the validation methodology should be similar for all detectors that mimic the functioning of loop detectors.
3.1 Types of detector errors

The following is a list of known errors that can be found in loop data and which this research explicitly seeks to identify. The list may not be comprehensive but includes the predominant errors. The rising and falling edges mentioned here are defined in Figure 1.1.

- Premature rising edge: Vehicle is detected earlier than expected.
- Delayed falling edge: Vehicle’s presence is registered for more time than expected.
- Delayed rising edge: Vehicle is detected later than expected.
- Premature falling edge: Vehicle’s presence is registered for less time than expected.
- Flicker: Sensor output repeatedly turns on and off for some time.
- Missed vehicles: Vehicles pass undetected.
- Wrong detection: Vehicle is detected when actually there is none.

All of the errors may not be present in a particular dataset but they can be found if many datasets are observed. While the first two errors in the list extend on-time measurement, the next three reduce on-time. These errors could be due to various reasons like improper installation of detector hardware and/or software problems. The goal of the validation process is to identify all the known errors present in the data from both single as well as dual loop detectors, which is achieved by implementing a series of threshold value tests on the event data. The thresholds are of two types, the first to check if an individual vehicle measurement is acceptable. Of course it is unreasonable to expect all measurements to be acceptable; some transient errors are to be expected, e.g., a vehicle changing lanes over the detectors. To accommodate these expected errors, a second threshold is applied to the results of many applications of the first test, i.e., a minimum percentage acceptable. For
example, one threshold for minimum on-time test specifies the minimum feasible on-time while the percentage of on-times greater than minimum on-time must be above the minimum percentage acceptable for the test in order for the data to be accepted. If the data passes all the "important" tests, as defined later in this chapter, the detector is categorized as good and the data are deemed valid. Various tests are developed for single and dual loops separately. While the tests developed for a single loop can be applied to each loop in a dual loop, the redundant information from the two observations of each vehicle is exploited to develop additional tests for dual loop detectors. The next part of this chapter discusses the tests and their effectiveness in identifying detector errors.

3.2 Data and vehicle measurements

This chapter uses data from two sources to demonstrate the tests. First, 24 hours of detector actuations sampled at 240 Hz from 45 detector stations on I-70/I-71 in Columbus, Ohio and second, 24 hours detector actuations sampled at 60 Hz from dual loop detector stations in the Berkeley Highway Laboratory along I-80, north of Oakland, CA. Although an entire day’s data has been used to demonstrate the tests, any sample that is statistically significant could be used. For example, to implement the tests in real-time, a sample size of 1000 vehicles or 1 hour of data could be used, with minor modifications to control for congested conditions.

For all measurements that use information from the two loops in a dual loop detector, the corresponding pulses from a given vehicle at both loops need to be matched. For this study, each pulse at downstream loop is matched to most recent pulse seen at upstream loop. When the dual loop detector is working properly, the loop arrangement
makes it rare to observe two pulses at one loop without an intervening pulse at the other loop. As explained later, the error detection tests are sensitive to this assumption and flag error when this assumption breaks down. To increase robustness, tests could be reapplied with the matching of the pulses reversed, i.e., all upstream pulses being matched to the next downstream pulse. All of the individual vehicle measurements are calculated as explained in section 1.1.

3.3 Traffic detector validation tests

The first level of testing should verify that the detectors are reporting data. To this end, tests that check for activity at a detector could be implemented in real-time and could be applied both to single as well as dual loops. If a single loop does not observe vehicles for long a period, e.g., 15 minutes outside of late night hours, it would likely indicate a problem. In the case of dual loops, the number of pulses observed at one loop since the last pulse observed at the other loop can also be used to check if both loops are working properly. The next two sub-sections describe the various tests developed to detect less obvious errors at a detector. Most of the tests are simple enough that they could be implemented in real-time. As one might expect, some of the tests are less effective than others, while some are redundant, so the process of identifying important tests is discussed after the tests are presented.

3.3.1 Single loop Tests

*Mode of on-times:* As the name suggests, the objective of this test is to determine the mode value of the on-times during free flow conditions. During most of the day, vehicles are expected to be free flowing and the percentage of short passenger vehicles is greater than
that of long vehicles; the mode on-time observed should normally correspond to a passenger car moving at free flow velocity. For example, a 20 ft vehicle traveling at 65 mph would yield an on-time of 13/60 seconds (on-time = length/velocity, in 1/60 sec, the resolution of the data) and the mode on-time is expected to be around that value. To illustrate that the majority of the lengths of vehicles correspond to short vehicles, the cumulative distribution function of lengths of 1620 vehicles during free flow at station 4 in the Berkeley Highway Laboratory is plotted in Figure 3.1. It can be seen that about 90 percent of the vehicles have measured lengths between 18 and 22 ft. We can expect a little higher mode in the outer lanes since on-time is inversely proportional to velocity for a given vehicle length and normally the traffic in the outer lanes moves at slower velocity. Therefore, a mode on-time that falls in the range of 11/60-16/60 seconds is considered to be good. Any mode outside the expected range indicates either detector errors such as flicker or sensitivity problems.

Figure 3.1: Cumulative distribution function of measured vehicle lengths of all vehicles with on-times between 11/60 and 16/60 seconds during free flow.
**Under Minimum On-time:** Even during free flow there exists a maximum value for velocity and there will be very few vehicles, if any, traveling at a greater velocity. Given a particular vehicle length, the maximum value of velocity corresponds to a specific on-time. Hence, the minimum feasible on-time is obtained when a short passenger vehicle is assumed to travel at maximum velocity. For this study, the maximum velocity is assumed to be 85 mph, which translates into an on-time of $\frac{10}{60}$ seconds when a 20 ft vehicle length is used. This test will be helpful when the low on-times are not frequent enough to change the mode.

**Over Maximum On-time:** This test looks at the other extreme of on-times but now the analysis should be restricted to free flow conditions as the on-times for congested conditions can take large values because the vehicles are moving slowly over the detector. If congested conditions are defined as velocity below 45mph, the maximum feasible on-time during free flow is obtained for the longest feasible vehicle, an 80 ft truck, traveling at the threshold velocity (45 mph) is $\frac{72}{60}$ seconds. Where 45 mph is used as a conservative estimate of free flow velocity, all vehicles above this threshold would be traveling at or near free flow conditions. Almost all the on-times during free flow are expected to be less than the maximum on-time. If we see too many on-times over the threshold, it would indicate that the detector is sticking on.

**Under Minimum Off-time:** A driver normally maintains certain "safe" gap between their vehicle and a leading vehicle. In fact this gap varies with velocity. Figure 3.2 shows the variation of off-time, a measure of gap between vehicles, with velocity. However, it is possible to assume a critical gap (which translates into an off-time) during free flow such that all drivers exceed
this value. For this study, the safe gap is assumed to be an analytically conservative 22 ft, which corresponds to an off-time of \(\frac{20}{60}\) seconds by a vehicle traveling at 45 mph. Any gaps below the critical value are infeasible and if seen in the data indicate detector errors. Typically, low off-times can be attributed to pulse breakups, tailgating or flicker.

*Mode of Off-times:* The mode value of off-times is calculated in this test. We cannot expect mode off-time to fall within a specific range as seen in mode on-time test as the range could change with change in flow, weather, etc. However, if the mode off-time were less than the critical off-time (found out in the under minimum off-time test) then it would indicate that the problem causing low off-times is severe.

![Mode of Off-times](image)

*Figure 3.2: Measured velocity versus off-time at the first loop in a dual loop.*
Under Minimum Length: The effective vehicle length estimated as mentioned in Chapter 1 has a feasible range, which is assumed to be between 10 ft and 90 ft. This test flags an error if the effective vehicle length is lower than the minimum feasible value, i.e., 10 ft. A large percentage of infeasible vehicle lengths indicate a problem in the loop. Short vehicle lengths could be due to pulse break-ups, the detector set to pulse mode rather than presence mode, premature falling edge or similar errors.

Over Maximum Length: This test looks at the other extreme of the feasible length range. The percentage of vehicles with an effective length less than a maximum feasible value (90 ft) is calculated. A large percentage of infeasible long vehicles would indicate stuck on problems or similar errors.

3.3.2 Dual Loop Tests

Moving median velocity difference test: This test compares the individual vehicle velocity against the median of 11 velocity measurements centered on the given vehicle. If the difference between the two exceeds a preset threshold (1/4th of individual vehicle’s velocity for this study), the velocity measurement is considered erroneous. These errors could result in incorrect estimation of vehicle length. To avoid errors due to transient errors, moving median of measured velocities could be used. The process of eliminating transient errors is explained in detail later.

On-time difference: Coifman [9] developed this test to evaluate the loop sensor units and detect crosstalk between detectors. Assuming the dual loop is working properly, the on-times at
Figure 3.3: Distribution of on-time differences between upstream and downstream loops of a dual loop. On-time differences within 2/60 seconds are acceptable (A) Good distribution (B) Bad distribution
each detector should be the same during free flow, irrespective of vehicle’s length. But the two on-times will differ in the presence of many hardware and software problems, thus, the difference of on-times from each detector could be used to evaluate the performance of the dual loop. The maximum allowed difference between on-times is $\frac{2}{60}$ seconds. The percentage of vehicles with on-time differences less than the threshold value is calculated as a measure of proper functioning of the detectors. If the loops are functioning properly, only a small percentage of the differences should be over the threshold. Figure 3.3A shows the distribution of on-time differences for a properly working dual loop. Figure 3.3B shows the same for a dual loop that has problems.

*Off time difference:* This test is similar to the above test but uses off-times instead of on-times. This test takes advantage of the pulse matching methodology to identify detector errors. Consider the hypothetical example in Figure 3.4.

![Figure 3.4: Matching pulses between upstream and downstream loops at a dual loop.](image)

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Since all the pulses from second loop are matched to the most recent pulses from the first loop, \(d_2\) and \(d_3\) are both matched to \(u_2\). If the on-times of \(u_2\), \(d_2\) and \(d_3\) are comparable to each other, the error does not show up in the on-time difference test but is likely to be identified when off-time differences are examined. The percentage of off-time differences less than a threshold of \(10/60\) seconds gives an idea of the severity of the error.

**Under Minimum Distance:** This test is equivalent to the under minimum off-time test applied to the single loops. Since the vehicles during congestion could travel bumper-to-bumper, this test is only applied during free flow conditions. Measured velocity and off-times from each of the detectors are used to calculate the observed gaps between vehicles, which are compared to the assumed minimum safe gap of 22 ft. The percentage of vehicles with gap greater than a critical gap is calculated in this test. If we see too many short gaps, it may be indicative of flicker or similar errors.

**Under Minimum Length:** This test is similar to the minimum length test applied to single loops, except that measured velocity is used to calculate vehicle lengths instead of estimated velocity. The percentage of vehicles with length greater than the minimum feasible length is calculated in this test.

**Over Maximum Length:** Again, this test is similar to the maximum length test applied to single loops, but measured velocity is used to calculate vehicle lengths. The percentage of vehicles with length lesser than the minimum feasible length is calculated in this test.
**Mode On difference:** This test looks at the difference between the mode of on-times at upstream loop and the corresponding mode at the downstream loop during free flow conditions. If the loops are functioning properly, the difference should be zero. Providing a small tolerance, the difference of mode on-times must be within a threshold (≤2/60 seconds for this study) to pass this test.

**Mode Off difference:** This test is similar to the above test, but the difference in mode off-times is measured. The test is not restricted to free flow conditions, i.e., it is applied on entire day’s data. A threshold of 4/40 seconds is used for this test. The threshold for this test is looser than that of the mode on-time difference test because off-times cannot be controlled.

**Median On-time and Off-time differences:** Median of on-times and off-times are calculated at each loop and the differences between the measures from each loop are examined. These tests would indicate the severity of the problem that is identified by on-time difference and off-time difference tests. The current thresholds are 3/60 and 5/60 seconds for median on and median off difference tests respectively.

### 3.4 Thresholds

Tables 3.1 and 3.2 summarize the thresholds used in this study for Single loop and Dual loop tests, respectively, i.e., acceptable measurements and minimum percentage acceptable for each test. It is important to note that these thresholds may vary with location and may need to be calibrated to suit the requirements of a specification, but such a task should not be difficult. Instead of just specifying whether a detector passes or fails a test, a third
“border” category is introduced to identify detectors that could fail the test if performance degrades a little. The ranges for classifying the detectors were fixed in order to highlight detectors that perform poorly in each test from the existing set of detectors. Also, tighter ranges are adopted for tests that identify the problems that lead to severe performance degradation. For example, the ranges for maximum on-time test are very tight when compared to other tests, such as minimum on-time test. Results for each test from 45 days from both I-70/71 and BHL data are observed to verify that all the problem detectors were identified with the current set of thresholds.

<table>
<thead>
<tr>
<th>Single Loop Test</th>
<th>Acceptable Measurement</th>
<th>Minimum Percent Acceptable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Fail</td>
</tr>
<tr>
<td>Minimum On-time</td>
<td>10/60 sec</td>
<td>&lt;95</td>
</tr>
<tr>
<td>Maximum On-time</td>
<td>75/60 sec</td>
<td>&lt;98</td>
</tr>
<tr>
<td>Minimum Off-time</td>
<td>20/60 sec</td>
<td>&lt;95</td>
</tr>
<tr>
<td>Minimum Length</td>
<td>10 ft</td>
<td>&lt;98</td>
</tr>
<tr>
<td>Maximum Length</td>
<td>90 ft</td>
<td>&lt;99</td>
</tr>
<tr>
<td>Mode On-time</td>
<td>11/60-16/60 sec</td>
<td>-</td>
</tr>
<tr>
<td>Mode Off-time</td>
<td>&gt;20/60 sec</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3.1: Summary of thresholds for all Single loop tests
<table>
<thead>
<tr>
<th>Dual Loop Test</th>
<th>Acceptable Measurement</th>
<th>Minimum Percent Acceptable</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Fail</td>
</tr>
<tr>
<td>Moving Median Velocity</td>
<td>1/4 current vehicle’s velocity</td>
<td>&lt;98</td>
</tr>
<tr>
<td>difference</td>
<td></td>
<td></td>
</tr>
<tr>
<td>On-time difference</td>
<td>2/60 sec</td>
<td>&lt;95</td>
</tr>
<tr>
<td>Off-time difference</td>
<td>10/60 sec</td>
<td>&lt;95</td>
</tr>
<tr>
<td>Minimum Distance</td>
<td>22 ft</td>
<td>&lt;98</td>
</tr>
<tr>
<td>Minimum Length</td>
<td>10 ft</td>
<td>&lt;98</td>
</tr>
<tr>
<td>Maximum Length</td>
<td>90 ft</td>
<td>&lt;99</td>
</tr>
<tr>
<td>Mode On-time difference</td>
<td>2/60 sec</td>
<td></td>
</tr>
<tr>
<td>Mode Off-time difference</td>
<td>4/60 sec</td>
<td></td>
</tr>
<tr>
<td>Median On-time difference</td>
<td>3/60 sec</td>
<td></td>
</tr>
<tr>
<td>Median Off-time difference</td>
<td>5/60 sec</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.2: Summary of thresholds for all Dual loop tests.

3.5 Visualization of test results

For a small number of detectors it is easy to look at a table of results, i.e., percentage of individual vehicles passing each detector, for each test to identify detectors that fail. But as the number of detectors increases, it is inconvenient to identify problems by looking at a table and it is possible to overlook some of the problem detectors. For example, the table for I-70/71 would contain about 60 rows (28 single detector stations and 17 dual detector stations) and 10 columns (maximum of 5 lanes per direction). To make the identification process easy, color-coded plots are developed both for single loop tests and dual loop tests, i.e., a detector is given a color based on the predefined range (passing percentages or values) in which the test results fall. Sample plots in Figures 3.5 and 3.6 show minimum on-time and on-time difference tests, respectively, to give an idea of what is intended. The ranges for assigning colors could be changed depending on the data being used. Figure 3.5 shows cells
for each detector oriented as if viewing the freeway from directly above, of course without any gaps in between. Thick vertical lines in the plots separate detector stations, while the dotted vertical lines separate the two loops in a dual loop. The two loops in a dual loop are arranged according to the direction of movement of traffic, i.e., as we move from left to right, we first see upstream loop (u) at station 102 in the Northbound plot, while we see downstream (d) loop first in the Southbound plot. To maintain clarity, all the station numbers are not shown. Also, the lanes are numbered from inside as per the convention of the operating agency. Figure 3.6 shows the results only for dual loop stations. Similar plots were developed for visualizing results from I-80 data but not shown here. Figures, which show whether a detector passes, fails or is on the border of failing in a given test, are developed to view the results by lane. The plot shown in Figure 3.7 shows the performance of lane 1 detectors for the entire suite of tests. Plots showing the results for other lanes are similar to Figure 3.7.
Figure 3.5: Color-coded plot to visualize Single loop validation test results for I-70/71 on April 23, 2002.
Figure 3.6: Color-coded plot to visualize Dual loop validation test results for I-70/71 on April 23, 2002.
Figure 3.7: Sample lane 1 color-coded plot to visualize all validation test results by lane for I-70/71 on April 23, 2002.
3.6 Fundamental tests

As noted earlier, some of the tests presented are less effective than others, while others are redundant. Also, the impact of failure of tests on aggregate parameters may vary for each test. Therefore, it is possible to identify a subset of tests that are fundamental to the working of a detector and these tests should not be failed. The idea behind picking fundamental tests is that if a detector passes these tests the data would give meaningful traffic parameters. It is important to note that perfect data is not guaranteed even if all the fundamental tests are passed. The discussion in the next two sections is based on observed test results from 45 days from both I-70/71 and I-80 data.

3.6.1 Single loops

On-time is the most important measurement from a single loop as most other traffic measures depend on it. Hence, tests that identify errors in on-time are important. While minimum and maximum on-time tests catch the extreme errors in on-time, the mode on-time test during free flow is necessary to make sure that majority of the on-times are reasonable, and thus, they are considered the most important tests. Even if the on-time tests are passed by a detector, it is important to ensure that the data are meaningful, for example, too many infeasible off-times would indicate error in the data. Therefore, minimum off-time test is the next important test. Since length at a single loop is estimated from on-times, errors caught by the length tests are a result of errors in on-time or velocity. As the on-time tests catch most of the severe problems, length tests are not as informative. The length tests are not entirely redundant and could be informative in some cases. For example, if a detector randomly sticks on a little longer or shorter than it should for some period of the day, the
problem might not appear in any of the on-time tests but can show up in the length tests assuming that velocity is measured or estimating correctly. Figure 3.8 shows the plot of estimated length versus on-time at a single loop. Horizontal and vertical lines are drawn at the acceptable measurements for minimum and maximum length and on-time tests. The inclined line shows the boundary between congestion and free flow (45 mph). The arrows show the acceptable regions in the length-on-time plane. The regions circled highlight the data that failed the length tests. Figure 3.8 shows that the length tests are not redundant as on-time and off-time tests could not catch the errors circled in the plot. Finally, the mode off-time test is redundant and cannot be an important test as the problem is caught by minimum off-time test before it shows up in mode off-time test. Therefore, Mode On-time, Minimum On-time, Maximum On-time and Minimum Off-time tests are the single loop fundamental tests that should not be failed.

Figure 3.8: Thresholds of length and on-time tests shown in length - on-time plane. The arrows show the acceptable regions for the minimum and maximum length and on-time tests. The data in the circles is erroneous and is caught only by the length tests.
3.6.2 Dual Loops

The list of fundamental tests for dual loops can include single loop tests too as each loop can be individually subjected to single loop tests. On-time difference test is one of the most important dual loop tests. Failure of this test may be indicative of mismatching errors. But if both loops in a dual loop behave similarly, i.e., record errors in the same fashion, the errors go unnoticed. If both the detectors are set to pulse mode rather than presence mode, on-times observed will be shorter than expected but identical at each detector. Hence, the problem is not detected by this test and vehicle lengths will be underestimated. Vehicle lengths are also affected if on-times are either shorter or longer than what they should be.

The single loop based mode on-time test ensures that majority of the on-times are reasonable and assuming that traversal times are accurate, vehicle lengths will be calculated accurately. The calculation of vehicle lengths has to be accurate. For some applications, e.g., travel time estimation methodologies based on re-identification of vehicles use vehicle length as a vehicle’s signature [21]. Any errors in vehicle lengths would reduce the number of re-identified vehicles and thus the accuracy of estimated travel time. If one of the detectors detects extra vehicles or misses vehicles, the above two tests cannot catch this problem because of the current matching methodology. Moving median velocity difference test takes advantage of the matching methodology and flags error when the problem of extra or missing vehicles occurs at one of the detectors. Also, this is the only test that directly identifies problems in traversal times. For example, if the second loop occasionally detects vehicles a little earlier than it should, traversal times are reduced and velocity is overestimated. This error could lead to unexpected length distributions and any applications based on length are affected. The median and mode on-time difference tests are redundant.
because on-time difference test captures those errors and both the tests flag error only if the problem is severe. Moving median velocity difference test catches most of the errors due to off-time discrepancies and thus not effective even though not entirely redundant. Off-time difference test becomes useless if the pulses are matched on one-to-one basis. Median and mode off-time difference tests flag errors only when problems are serious. The maximum and minimum length tests flag error when there are errors in either velocity or on-time and will be useful only if the on-time errors are not frequent enough to change the mode. Finally, under minimum distance highlights errors due to off-times or velocity and is redundant since the moving median velocity difference test and off-time difference test will catch most of the errors. Therefore, the fundamental dual loop tests are On-time difference, Mode On-time and Moving Median Velocity difference.

3.7 Order to pick tests

It may be sometimes desired to implement as few tests as possible to catch major problems in the data, for example, to reduce the analysis time when working in real-time. The following two sections identify the test(s) to be picked, given that there is a limitation on the number of tests.

3.7.1 Single loops

If only one test can be implemented, then it should be the mode on-time test during free flow so that vehicle lengths and velocity estimates could be reasonable. If the mode is higher than expected, it indicates a stuck-on problem or similar errors and if it is lower than expected, it indicates premature falling edge, flicker, detector set to pulse mode or similar
errors. Flow and occupancy may not be accurate even if the data passes this test because problems like pulse break-ups can go unnoticed if they are not serious enough to change mode on-time and extra vehicles cannot be detected using this test.

If two tests have to be implemented, then pick the mode on-time and the under minimum off-time tests. The above two tests catch serious on-time errors and infeasible vehicle actuations. Errors such as pulse break-ups or flicker could be caught using the minimum off-time test.

If three tests have to be implemented, then pick the mode on-time and the under minimum off-time tests and one of the on-time tests depending on the mode, i.e., even if the mode is satisfactory, one of the on-time tests could be picked depending on where the mode falls in the satisfactory range. For example, if the mode is closer to the lower bound of the range, pick minimum on-time test.

### 3.7.2 Dual loops

If only one test has to be implemented, then it should be the on-time difference test. If a detector passes this test, we should not expect many of the potentially major problems to be present.

If two tests have to be implemented, then the on-time difference test and mode on-time test can be picked. If both the loops in a dual loop are set to pulse mode, on-time difference test cannot identify the problem but the mode on-time is likely to catch it.

If three tests have to be implemented, then pick the on-time difference test, the mode on-time test and the moving median velocity difference test, i.e., all three dual loop
fundamental tests. If we miss vehicles at upstream loop and/or detect extra vehicles at downstream loop, moving median velocity difference test is likely to identify the problem.

3.8 Data Cleaning

This section discusses some of the data cleaning processes to correct for errors related to detector sensitivities, incorrect dual loop spacing and underestimation of single loop velocity during low flow conditions.

3.8.1 Correction Factors

On-time at a single loop detector is directly proportional to the sensitivity of the detector. As velocity is estimated at a single loop, changes in detector sensitivity lead to scaling errors in velocity because a constant vehicle length is assumed. Similar scaling errors occur at a dual loop when incorrect loop spacing is used. It is possible to correct for such errors by determining a correction factor for loop spacing in case of a dual loop and for on-time in case of a single loop. It should be obvious that this error affects both aggregated velocity and occupancy but not flow. Correction factors can be determined by taking advantage of the fact that the velocities during free flow are almost constant and assuming that the constant value corresponds to posted speed limit. Since any location typically observes congestion only for few hours every day, the median value of velocities for a day should fall into free flow category and hence should be comparable to posted speed limit, i.e., if median velocity for a day is 60 mph and posted speed limit is 65 mph, we need a correction factor of 1.083 (65/60). If greater accuracy is desired, actual velocities could be measured with a radar gun. If a location normally sees congestion for more than half of a day, the process could be
applied to velocities during known free flow periods. The correction factor for on-time will be the reciprocal of the correction factor for velocity at a single loop since on-time is in the denominator in Equation 1.4. Occupancy is therefore scaled by the inverse of the velocity correction factor. For dual loops, the correction factors for occupancy are found out for each loop individually using estimated velocity but the correction factor for velocity is obtained from measured velocities. Figures 3.9A, B show the results of using correction factors at a single loop. Note the correction in velocities over the 24 hours from an infeasible 100 mph to a speed close to the posted speed limit. The results for a dual loop would be similar.

Figure 3.9: Effect of correction factors at a single loop (A) Five minute aggregated estimated velocity before and after correction (B) Occupancy before and after correction
3.8.2 Occupancy Filter

Single loop velocity is estimated using Equation 1.4 could lead to errors during low flow periods as the center of the sample distribution might differ from the expected values because of the small number of vehicles per sample. But the occupancies during such low flow conditions should be below 10 percent. As shown by Coifman [11] and seen in Figures 3.9A and B, occupancies less than 10 percent should correspond to free flow conditions. Therefore, the velocities for the periods with occupancy less than 10 percent could be set to an assumed free flow velocity. The occupancy threshold could be used to overcome velocity estimation errors during low flow periods at a single loop. Figure 3.10 shows the performance of the occupancy filter. One of the loops in a dual loop is used to mimic a single loop so that estimated velocities could be compared with dual loop velocities.

![Performance of an occupancy filter at a single loop.](image)

Figure 3.10: Performance of an occupancy filter at a single loop.
3.8.3 Moving median velocity

As noted earlier, moving median velocity could be used at a dual loop instead of actual measured velocities to replace any transient errors in the data with median values from the 11 most recent measurements, up to and including the current vehicle. Figure 3.11 shows the time series individual vehicle velocities at a dual loop and the resulting velocities after applying moving median filter with a sample size of 11 vehicles centered on the current vehicle.

![Figure 3.11: Cleaning velocities using moving median filter.](image-url)
3.8.4 Pulse break-ups

As the name suggests, pulse break-up implies breaking of a single pulse into two or more pulses. They usually occur when trucks or vehicles with trailers pass over a detector. As Chen and May [8] indicate, pulse break-ups are inevitable at any loop detector. They could be corrected using software because, typically, pulse break-ups are associated with low off-times and hence could be identified. If the off-time between two adjacent pulses is infeasible and the resulting on-time after joining the two pulses is reasonable, the two pulses could be treated as coming from a single vehicle by removing the off-time between them. Thus, errors in flow would also decrease.
CHAPTER 4

IMPROVED SINGLE LOOP VELOCITY AND TRAVEL TIME ESTIMATION

Poor velocity estimation at single loops can lead to unexpected and undesirable results when interpreted. The first section of this chapter develops a hybrid methodology to estimate velocity accurately using data from a single loop detector in the presence of heavy truck traffic, where most of the existing methodologies fail. The second section presents a simple travel time estimation methodology, which uses cleaner event data and single loop velocity estimates. The proposed methodology is meant for offline purposes as it uses information after a vehicle’s departure to estimate its travel time, as explained herein.

4.1 Single loop velocity estimation

The conventional method of estimating single loop velocity involves Equation 1.3. As will be discussed shortly, Equation 1.3 can yield poor results when the true but unknown average vehicle length varies.

For this study, 24 hours of detector actuations sampled at 240 Hz from 17 dual loop detector stations on I-70/I-71 in Columbus, Ohio are used. Dual loops provide both single loop data and measured vehicle velocities to verify single loop velocity estimates. To mimic a
single loop, only the upstream loop data in a given dual loop is used to estimate velocities in that lane. Figure 4.1A shows the plot of velocity estimated using Equation 1.3 with a sampling period of T=30 seconds. The estimates are very noisy, with an average absolute error of 6.26 mph after correcting for bias due to length. This correction process will be discussed shortly. For now, it is sufficient to note that the errors would be larger without eliminating the bias, and in any event, the individual errors would scale linearly with L. These results are consistent with Coifman (2001), which showed that the assumption of constant vehicle length could lead to poor estimates because a sample’s vehicles can differ from the assumed average vehicle length. The true effective vehicle lengths vary from 20ft to 80ft and thus, average vehicle length in a sample can vary too. If all the vehicles passing a detector were long, then there would be no problem in estimating velocities, as we just need to assume a different constant length. The presence of varying vehicle lengths skews occupancy and hence velocity estimates from one sample to the next. Coifman et al (2003) has shown that using Equation 1.4 to estimate the median velocity instead of the mean velocity from Equation 1.3 can reduce the effect of long vehicles in a sample, as the median is less sensitive to outliers than mean. This change can lead to significant improvements when long vehicles are below 10 or 15 percent of the passing traffic. Figure 4.1B shows the results from Equation 1.4 applied to the same raw detector actuations as Figure 4.1A, with a moving sample size of 11 vehicles ending with the current vehicle. The average absolute error after correcting for bias due to length dropped to 3.15 mph. Repeating this analysis at a detector station with heavy truck traffic (40 percent of the vehicles are longer than 30 ft), Figure 4.1C-D show the performance from Equation 1.3 and 1.4, respectively, to the same day of raw detector actuations at this detector. The conventional estimate from Equation 1.3 has an average absolute error of 25.88 mph while Equation 1.4 has an average absolute error of
23.84 mph. Once more we corrected for the bias due to length in both plots. Figure 4.2 shows the distribution of measured vehicle lengths for the entire day, from the dual loop detector used in Figure 4.1C-D.

To remove the bias in Figure 4.1 we used the on-time distribution during free flow periods ($v > 45$ mph). Since all vehicles have roughly the same speed, the distributions of on-times look very similar to Figure 4.2, with the mode corresponding to a short vehicle. For each detector, the mode on-time was used to estimate $L$ assuming the vehicle traveled at the posted speed limit, yielding $L=24$ ft for the "typical" detector and $L=20$ ft for the detector with heavy truck traffic. This supposition was verified by examining the true lengths from the dual loop detector as well. As one might expect, the errors shown in Figure 4.1 most frequent during the early morning (12 midnight to 5 AM) because the flow of short passenger vehicles decreases.

Although Equation 1.4 improved performance at the "typical" detector, even after removing the bias, both of the methods performed poorly at the detector with heavy truck traffic. This study introduces a way to obtain reliable estimates of velocities in the presence of such heavy truck flows using the velocity estimates from Equation 1.4 in conjunction with basic traffic flow theory assumptions.
Figure 4.1: Comparison of aggregated estimated versus measured velocities for T=30sec (A) Traditional and (B) moving median with N=11 vehicles, for a typical detector, (C) Traditional and (D) moving median with N=11 vehicles, for a detector with heavy truck flows.
4.1.1 Finding Vehicle Sequences

The velocities of two successive vehicles should usually be close to one another even under congestion, e.g., Figure 4.3 shows a scatter plot comparing the measured velocity of successive vehicles for an entire day at one detector. Since each vehicle’s on-time is proportional to its length, the ratio of successive on-times should be close to the corresponding ratio between the unknown vehicle lengths. For example, the ratio of on-times of successive passenger cars will be close to 1, while the ratio of on-times of a car followed by a truck differs from 1, proportional to the ratio of their lengths. From Figure 4.2, we see that the typical passenger vehicle has a length of approximately 20 ft while the longest trucks are about 80 ft. We would expect the maximum ratio to occur at these extremes, i.e., 4. Assuming that there are no detector errors, we will only see this on-time ratio of 4 whenever
a car is immediately followed by long truck. Thus, although we cannot measure length directly, we can deduce it when observing these extreme on-time ratios. This idea is exploited to find sequences of long and short vehicles when they are moving together in traffic. Two such sequences, short vehicle followed by a long vehicle (SL) and long vehicle followed by a short vehicle (LS), are identified by comparing the ratio of on-times of

![Figure 4.3: Velocities of successive vehicles are close to each other. The outer lines show the 10 mph bounds.](image-url)
successive vehicles. This length ratio is site-specific and when dual loops are available elsewhere on the facility, it can be obtained from the measured distribution of vehicle lengths. These distributions are usually bimodal, with strong narrow peak for short vehicles and a broader peak for long vehicles. We can find the mode length for both peaks to derive the ratio. When dual loop detectors are not available, we can do the same process using the distribution of on-times measured during known free flow periods. In either case, after establishing the optimal ratio, instead of using just one value, a range is used to accommodate for the small variations in the lengths and velocities of vehicles. During free flow periods, short vehicles often travel at slightly higher velocities than trucks. Thus, specifying a range potentially increases the number of sequences found. The following subsection will discuss more about setting this range. Once the range of the ratio is established with the lower and upper bounds (LB and UB respectively), the SL and LS sequences can be found in the time series of on-times as follows:

\[
\text{If } LB \leq \frac{on_i}{on_{i-1}} \leq UB, \text{ then a SL sequence has been observed.}
\]

\[
\text{If } LB \leq \frac{on_{i-1}}{on_i} \leq UB, \text{ then a LS sequence has been observed.}
\]

where, \( on_{i-1} \) is the on-time of \((i-1)^{th}\) vehicle and \( on_i \) is the on-time of \(i^{th}\) vehicle.

We can calculate the individual velocities for the vehicles in the sequences using,

\[
\hat{V}_s = \frac{L_s}{on_s} \quad \text{and} \quad \hat{V}_L = \frac{L_L}{on_L}
\]

where \( L_s \) and \( L_L \) are mode lengths of measured or estimated length distribution, as discussed above.
4.1.2 Finding the Optimal ratio

For the stations considered here, the mode for short on-times is 13/60 sec and for long on-times is 50/60 sec during known free flow periods and their ratio is close to 4. For lower ratios, between 2.5 – 3.5, the errors in estimated velocity for the resulting sequences were high. This outcome should be expected, as the long vehicle length in estimating the velocity is assumed to be 80 ft, but many vehicles in the 40 – 60 ft range showed up in the on-times with that range. As the ratio range moves towards 6, the number of sequences identified reduces, since it exceeds the maximum feasible length of a vehicle. Several ranges were tried and based on the number of sequences and the severity of the errors of those sequences we adopted 3.5-4.5 as the range to be used.

4.1.3 Accuracy of the velocity from sequences

To evaluate the performance of conventional estimates, Equation 1.3, median on-time estimates, Equation 1.4, and the new method, we use two measures of error, average absolute percentage error (AAPE) and bias. They are defined as follows:

\[
AAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{v}_i - v_i^*}{v_i} \right| \times 100
\]

\[
Bias = \frac{1}{n} \sum_{i=1}^{n} (\hat{v}_i - v_i^*)
\]

(4.3)  (4.4)

where \(v_i^*\) is the true value of the estimate \(\hat{v}_i\) for vehicle \(i\). The error for the sequences is calculated by comparing the individual velocities of sequences to the corresponding measured velocities. Velocity from the conventional method is calculated using Equation 1.3
with $T=30$ seconds. Sequences do not fall in every 30 sec sample; so, we restrict ourselves to those samples in which the sequences fall when calculating the error for the conventional method estimates. The velocities of those samples are then compared to the corresponding 30 sec aggregated measured velocities. In the case of Equation 1.4, velocity for the current vehicle is calculated using the median on-time of the current vehicle and the 10 vehicles preceding it. Then, the velocities are compared to the moving median measured velocities using the same sample of 11 vehicles. Table 4.1 shows the accuracy of these velocity estimates for sequences as compared to the conventional and median on-time estimates.

4.1.4 Extensions

A sequence where a short vehicle is followed by long followed by another short vehicle (SLS) can also be identified. The number of SLS sequences found in a day is significantly lower compared to that of SL or LS. Though all SLS include either an SL or LS, it is useful to identify them because they are more robust to detector errors. In any event, the number of sequences SL, LS and SLS found is limited and we cannot capture all of them. The average headway between two sequences ranged between less than a minute to 50 minutes in 5 days of data for 17 stations. The ratio of on-times of many of the actual sequences may fall just outside the range, and thus, are ignored. In an attempt to capture some of these otherwise discarded sequences, two more sequences are identified where a long vehicle and short vehicle are separated by a medium length vehicle. We increase the number of sequences by applying the same logic that is used to identify SL and LS but skip a vehicle in-between. The two sequences are short vehicle followed by a medium length vehicle followed...
by a long vehicle (SL2) and long vehicle followed by a medium length vehicle followed by a short vehicle (LS2), which can be identified as follows:

If $LB \leq \frac{on_{i}}{on_{i-2}} \leq UB$, then a SL2 sequence has been observed.

If $LB \leq \frac{on_{i-2}}{on_{i}} \leq UB$, then a LS2 sequence has been observed.

where, $on_{i-2}$ and $on_{i}$ are the on-times of $(i-2)^{th}$ and $i^{th}$ vehicle respectively. Table 4.2 shows the accuracy of the three new sequences.

4.1.5 Finding the traffic state of vehicles

This new method of finding sequences is sensitive to detector errors as we are comparing the ratio on-times. The number of false sequences identified increases with an increase in the detector errors such as flicker or pulse break-ups. For example, an on-time that is terminated prematurely may be a quarter of the duration of a normal short vehicle, resulting in an erroneous SL or LS. So, it is important to eliminate as many such detector errors as possible, for example, removing unreasonably short on-times from the data. We can assume a maximum feasible velocity for the shortest possible vehicle, which corresponds to the minimum feasible on-time, anything shorter can be regarded as erroneous. Similarly, we can arrive at the maximum on-time possible during free flow. Coifman and Dhoorjaty (in press) [3] developed validation tests for both single and dual loop detectors, which can be used to find the severity of errors in the data. If such errors are too frequent, the detector may require field maintenance. Otherwise, these tests can be used to eliminate transient errors, as follows. Coarse measures of traffic state can help reduce the impact of occasional detector errors. From the individual vehicle measurements it is possible to establish whether traffic is
congested or free flowing. Relatively short on-times and occasional long off-times (the time gap between two successive vehicles, i.e., the time during which the detector is unoccupied) characterize free flow traffic, while the occasional on-time that is excessively long characterizes congested traffic. We can observe the characteristics of on and off-times over a window of 11 vehicles ending on the current vehicle to determine its state. Figures 4.4 and 4.5 show scatter plots comparing several of these metrics versus measured velocity. From these figures we establish that a vehicle must be in free flow conditions (velocity > 45 mph), if it satisfies all of the tests below (over a 11 vehicle window):

\[
\text{Minimum off-time} > T_1 = \frac{100}{60} \text{ sec} \\
\text{Maximum off-time} > T_2 = \frac{1500}{60} \text{ sec} \\
\text{Standard deviation of off-times} > T_3 = \frac{400}{60} \text{ sec} \\
\text{Median off-time} > T_4 = \frac{400}{60} \text{ sec}
\]

where standard deviation \( s \) is defined as follows:

\[
s = \left( \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)^{\frac{1}{2}} \quad \text{and} \quad \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{4.5}
\]

\( T_1, T_2, T_3 \) and \( T_4 \) can be determined by observing the data for many days. Note that this test is not intended to find all free flow vehicles, just distinct free flow vehicles.

After excluding all vehicles labeled free flow by the previous test, a vehicle must be in congested conditions (velocity < 45 mph), if it satisfies all of the tests below:

\[
\text{Minimum on-time} > T_5 = \frac{30}{60} \text{ sec} \\
\text{Maximum on-time} > T_6 = \frac{100}{60} \text{ sec} \\
\text{Individual vehicle occupancy} > T_7 = \frac{40}{60} \text{ sec} \\
\text{Standard deviation of on-times} > T_8 = \frac{45}{60} \text{ sec}
\]

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where, \[ \frac{\text{on-time} \times 100}{\text{on-time} + \text{off-time preceding on-time}} \] gives the individual vehicle occupancy.

\( T_5, T_6, T_7 \) and \( T_8 \) can be determined by observing the data for many days.

These steps provide information on 10-15 percent of the vehicles for our study cases, which can be used to verify estimated velocities in the estimation process. When a sequence and this coarse measure of traffic state are conflicting, the sequence is discarded. The next section explains more about the new estimation process.
<table>
<thead>
<tr>
<th></th>
<th>Congestion</th>
<th></th>
<th>Free flow</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L*q/occ</td>
<td>SL</td>
<td>MM</td>
<td>L*q/occ</td>
</tr>
<tr>
<td></td>
<td>AAPE</td>
<td>Bias</td>
<td>AAPE</td>
<td>Bias</td>
</tr>
<tr>
<td>Long</td>
<td>13.39</td>
<td>1.26</td>
<td>10.74</td>
<td>-2.54</td>
</tr>
<tr>
<td>Short</td>
<td>13.39</td>
<td>1.26</td>
<td>6.16</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Table 4.1: Comparison of AAPE and Bias for all the three methods, conventional (L*q/occ), sequences (SL and LS) and moving median (MM) for an entire day of data

<table>
<thead>
<tr>
<th></th>
<th>Congestion</th>
<th></th>
<th>Free flow</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L*q/occ</td>
<td>SLS</td>
<td>MM</td>
<td>L*q/occ</td>
</tr>
<tr>
<td></td>
<td>AAPE</td>
<td>Bias</td>
<td>AAPE</td>
<td>Bias</td>
</tr>
<tr>
<td>Long</td>
<td>13.90</td>
<td>1.35</td>
<td>10.74</td>
<td>-2.01</td>
</tr>
<tr>
<td>Short</td>
<td>13.90</td>
<td>1.35</td>
<td>5.18</td>
<td>1.04</td>
</tr>
</tbody>
</table>

Table 4.2: Comparison of AAPE and Bias for all the three methods, conventional (L*q/occ), sequences (SLS, SL2 and LS2) and moving median (MM) for an entire day of data
Figure 4.4: The characteristics of off-times within a window of 11 vehicles. (A) min off-time Vs velocity, (B) max off-time Vs velocity, (C) standard deviation of off-times and (D) median off-time Vs velocity. The horizontal lines represent the thresholds and the vertical lines are drawn at 45 mph.
Figure 4.5: The characteristics of on-times within a window of 11 vehicles. (A) min on-time Vs velocity, (B) max on-time Vs velocity, (C) individual vehicle occupancy Vs velocity and (D) standard deviation of off-times. The horizontal lines represent the thresholds and the vertical lines are drawn at 45 mph.
4.2 Estimating Velocity

The velocity estimates from Equation 1.4 are good under typical urban vehicle population but they are poor when there are heavy truck flows, i.e., in presence of significantly heterogeneous traffic. The new method provides good estimates under such vehicle mix conditions but only when a sequence passes, with occasional gaps in excess of 15 min. So here we develop a hybrid, which uses velocity estimates from Equation 1.4 and sequences to produce new aggregate velocity estimations for a given sample period T, set to 30 sec for illustrative purposes.

4.2.1 Aggregation process

Figure 4.6 shows the flow chart for the hybrid algorithm. We start with the current sample. Whenever sequences fall within that sample during aggregation, we trust their velocity estimates as we have eliminated most detector errors before finding sequences. If more than one sequence is observed, we take median of those sequences to further reduce the sensitivity to errors. When there are no sequences in the current sample, the median of velocity of any sequences within the preceding two minutes is used because traffic conditions do not normally change significantly within that time frame and a sampling period of 5 min has already been widely accepted for many applications with Equation 1.3. When there are no sequences in the current sample or within the preceding two minutes, we compare the median on-time estimate over the most
Figure 4.6: Flow chart for the hybrid method of estimating velocity
recent 11 vehicles for the last vehicle that falls within $T$ against any available information from the traffic state tests. If the median on-time estimate does not agree with the traffic state, e.g., median on velocity $< 45$ mph and the traffic state suggests free flow, all the vehicles in the sample must be long vehicles or majority of them are long and we failed to identify a sequence. We can then use the fixed assumed free flow velocity at the location of the detector as an estimate for the current sample. If there are no detector errors, the case where median on-time velocity $\geq 45$ and traffic state suggesting congested conditions should not be observable. If it is seen, we take the median of the sample velocities for the preceding 2 minutes and use it as an estimate for the current sample. In the case where no information from sequences or the coarse measure of traffic state is available for a sample, we can conclude vehicle lengths are homogeneous and short. Then, the median on-time estimate should be good. Whenever the median velocity of the sequences is close (within a predetermined threshold) to the velocity estimated using median on-time, the latter estimate is chosen since it has larger number of vehicles in the sample. This process is repeated for each sample.

4.3 Discussion

Data from 34 days was used to test the new hybrid method and the results presented here are typical for all the days. The new hybrid method of velocity estimation is first tested at a detector with a moderate flow of trucks and the majority of those are seen during early morning hours. Figure 4.7 shows the results from the hybrid method contrasted against the conventional (Equation 1.3) and moving median (Equation 1.4) estimates for two sampling criteria, 30 sec and 5 min over the same data set. Table 4.3 shows the performance of the
Figure 4.7: The performance of traditional (first column), moving median (second column) and the hybrid estimation method (third column) for a typical detector. A, B, C show the results for T=30 sec and D, E, F for T=5 min. All plots use the same raw detector actuations. The circles are drawn at the same regions to make the comparison easy.

<table>
<thead>
<tr>
<th></th>
<th>AAPE before bias removal</th>
<th>AAPE after bias removal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L*q/occ</td>
<td>MM</td>
</tr>
<tr>
<td>Free Flow</td>
<td>30.31</td>
<td>13.23</td>
</tr>
<tr>
<td>Congestion</td>
<td>26.01</td>
<td>26.39</td>
</tr>
</tbody>
</table>

Table 4.3: AAPE comparison of the three methods for a typical detector for T=30 sec. Note that the large AAPE during congestion corresponding to average absolute errors less than 5 mph
three methods for $T=30$ sec. Though the moving median method works better than traditional method for $T=30$ sec, as seen from the density of points in the region circled, it is still not able to eliminate all of the noise. The hybrid method performs the best in this case.

When the sampling period is increased to 5 min, all the three methods show similar results, potentially making the new method unnecessary. But, this situation changes when we see the results from a detector that has a truck flow of more than 40% of its daily traffic flow of 10,000 vehicles/day. One of the reasons for such high truck flow at this detector is due to location, which is outside the city's ring road and just after an exit for a major shopping center. So, most of the passenger car traffic that is seen in this lane at upstream stations does not pass this detector. This station is rarely congested; only incidents downstream of this station and bad weather will cause congestion at this location. Figure 4.8 shows the results for $T=30$ sec and 5 min. Table 4.4 shows the performance of the three methods for $T=30$ sec. Both the traditional and moving median estimates perform poorly at this location, while the new hybrid method shows significantly better performance. Even after increasing the sampling period to 5 min, both of the earlier methods show poor performance. We see surprisingly frequent errors for the traditional and moving median methods because they severely underestimate the velocities for many vehicles.

As noted earlier, Coifman (2001) has shown that velocity estimates could be improved by using an occupancy filter. Tables 4.5 and 4.6 show the errors after applying an occupancy filter with a threshold of 8% for the typical detector and detector with heavy truck flow, respectively. Though reduced when compared to the errors from Tables 4.3 and 4.4 before applying occupancy filter, we still see relatively high errors from Equation 1.3 in both cases, and Equation 1.4 at the detector with high truck flows.
Figure 4.8: The performance of traditional (first column), moving median (second column) and the hybrid estimation method (third column) for the detector with heavy truck flows. A, B, C show the results for $T=30$ sec and D, E, F for $T=5$ min. All plots use the same raw detector actuations. The circles are drawn at the same regions to make the comparison easy.

Table 4.4: AAPE comparison of the three methods for the detector with heavy truck flows for $T=30$ sec. Note that this detector is rarely congested and hence the results are shown only for free flow.
Table 4.5: AAPE comparison of the three methods for a typical detector for $T=30$ sec after using an occupancy filter with a threshold of 8%.

<table>
<thead>
<tr>
<th></th>
<th>AAPE before bias removal</th>
<th>AAPE after bias removal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$L^*q/occ$</td>
<td>MM</td>
</tr>
<tr>
<td>Free Flow</td>
<td>23.80</td>
<td>10.42</td>
</tr>
<tr>
<td>Congestion</td>
<td>26.01</td>
<td>26.39</td>
</tr>
</tbody>
</table>

Table 4.6: AAPE comparison of the three methods for the detector with heavy truck flows for $T=30$ sec after using an occupancy filter with a threshold of 8%.

<table>
<thead>
<tr>
<th></th>
<th>AAPE before bias removal</th>
<th>AAPE after bias removal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$L^*q/occ$</td>
<td>MM</td>
</tr>
<tr>
<td>Free Flow</td>
<td>25.77</td>
<td>23.58</td>
</tr>
</tbody>
</table>

Figure 4.9 shows the cumulative distribution function for the errors, $v_i^* - \hat{v}_i$, for each of the three estimation methods from a month of data at the two detectors presented in Figure 4.1. Specifically, Figure 4.9 A, C show the results before and after correcting for bias, respectively, for a detector with truck flow around 10 percent of the vehicle fleet. Figure 4.9 B, D repeat the process for a detector with heavy truck traffic. It can be seen that the new method performs better than traditional as well as moving median method at both detectors, with a significant improvement when heavy truck traffic is present. Note that the lengths used in Figure 4.9 A, B differ as mentioned in the introduction, however, the real comparison of the three methods is the variance in the distributions shown in Figures 9 C, D after removing...
the bias. Table 4.7 summarizes the errors seen for each method and the length needed to eliminate bias.

The disadvantage of current method is the sampling criterion used in the estimating velocities from Equation 1.4. During low flow conditions, the time elapsed between the current vehicle and 10th vehicle prior to that could be large. To eliminate the use of data that is too old, a better sampling criterion could be used. For example, use the previous 11 vehicles only if all of those are within a predetermined threshold of time from the current time, otherwise, use all vehicles that pass the detector within that time frame.

<table>
<thead>
<tr>
<th></th>
<th>Typical Detector</th>
<th></th>
<th>Detector with heavy truck traffic</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Error</td>
<td>Length (ft)</td>
<td>Mean Error</td>
<td>Length (ft)</td>
</tr>
<tr>
<td></td>
<td>(mph) L=24 ft</td>
<td>Mean error=0</td>
<td>L=24 ft</td>
<td>Mean error=0</td>
</tr>
<tr>
<td>L*q/occ</td>
<td>16.68</td>
<td>35.84</td>
<td>35.94</td>
<td>48.41</td>
</tr>
<tr>
<td>MM</td>
<td>-2.94</td>
<td>22.69</td>
<td>29.19</td>
<td>38.56</td>
</tr>
<tr>
<td>Hybrid</td>
<td>-1.69</td>
<td>23.23</td>
<td>1.62</td>
<td>20.54</td>
</tr>
</tbody>
</table>

Table 4.7: Mean errors for traditional, moving median and hybrid estimation methods for a month of data. The results are shown for L=24 ft and 20 ft, and repeated for L that eliminates bias
Figure 4.9: Distribution of errors for traditional, moving median and hybrid velocity estimation methods for an entire month of data (A) and (C) show error distribution before and after correcting for bias for a typical detector (B) and (D) show error distribution before correcting for bias for a detector with heavy truck traffic. Text in (A) and (B) shows mean error for each method, while text in (C) and (D) shows length that made mean error zero for each method.
4.4 Travel time estimation

This section discusses a method to estimate travel time that is intended for offline purposes. The accuracy of the estimated travel times between two detector locations using loop detector data depends on the quality of the data. As the velocity at single loops is often underestimated, as explained earlier this chapter, many methodologies may overestimate travel time. The proposed methodology to estimate travel time is improved in the sense that it uses a cleaner set of velocities. Single loop velocity is estimated using the algorithm of the last section, scaling errors are corrected and an occupancy filter is used. As the loop detector stations are located at known intervals (about 0.3 miles apart on I-71), it is possible to segment the distance between origin (O) and destination (D), with each segment starting midway between adjacent detector stations. It is assumed that local conditions at a detector station apply to an entire section between stations. It can be seen that the travel time between O and D is the sum of time taken to travel each section in between them. However, the current method cannot account for any delay that is observed between detector stations even if the local velocities are perfect, for example, congestion due to vehicles exiting the freeway that does not backup until the detector station. This method of estimating travel time by dividing the freeway into sections is not new [29, 33, 34], and has been used by few others earlier. The following section explains the methodology in detail.

4.4.1 Methodology

Figure 4.10 shows the representation of velocity in time-space plane as segmented by sections and sample periods. To obtain the estimated travel time between O and D at a given starting time, a virtual vehicle is allowed to “move” in the time space plane with a
Figure 4.10: Trajectory of a virtual vehicle in the time-space plane. The circled region highlights the event where the virtual vehicle crosses a time boundary.
velocity obtained from the starting time and segment of O. The vehicle is allowed to move until it hits a boundary in time (next sample) or space (next segment) after which it continues to move with a new velocity determined by its current time and segment. Whenever the virtual vehicle leaves a segment, \( i \), its segment travel time, \( t_i \), is calculated. The process is repeated till \( D \) is reached and the total travel time is calculated by summing the individual segment travel times. It can be expressed as follows:

\[
t_{oo} = \sum_{i} t_i
\]  

(4.5)

where, \( t_{oo} \) = estimated travel time between origin (O) and destination (D)

\[
t_i = i^{th} \text{ segment travel time}
\]

The estimates from this methodology are more representative of those experienced by drivers than estimates obtained using segment velocities all measured at the same instant because the traffic conditions may change before destination is reached, especially during congested conditions. As the current methodology uses velocities from the future to estimate a departing vehicles’ travel time, it cannot provide travel times for vehicles just entering the section.

4.4.2 Travel time profiles

It may be helpful to drivers to know the variation of travel time between their origin and destination (on the freeway) as a function of time of day, so that they could adjust their travel to experience minimum delay. To this end, travel times are estimated using the methodology from 4.2.1 for every 5 minutes throughout the day for all weekdays of August 2003 using 5 minute aggregated data from I70-I71. The distances between origin and destination pairs on the freeway are shown in tables 4.8 and 4.9 for northbound and
southbound travel respectively. Figure 4.11A shows the variation of travel time as a function of time of day, with clean data. Correction factors and occupancy filter, explained in the previous chapter, are used to improve the accuracy of velocities. Figure 4.11B shows the resulting estimates without correction factors and occupancy filter. We can see the difference in travel times especially in the early morning period (1 am-5 am) and in the peak around 17:00 hours, though the difference during peak period is small when compared to the early morning period. During the early morning periods we expect the travel time to be roughly constant because of the free flow conditions, as seen in Figure 4.11A. The variation in travel time during early morning seen in Figure 4.11B is counter-intuitive. However, this comparison is not enough to say that the estimates from cleaner velocities are accurate. An attempt is made later in this section to compare the travel time estimates with those of a GPS equipped probe vehicle to find out the accuracy of the estimates. Figures 4.12 and 4.13 show the variation of travel time as a function of time of day for Northbound and Southbound travel respectively for various origin and destination pairs. As expected, we see an increase in travel time during morning and evening peak hours. These profiles could become a part of a travel time database, which are accessed to provide historical travel times between desired origin and destinations. Also, the historical travel times could be used as a reference for travel times estimated in real-time and severe deviations from the historical travel times would be a suspect.

<table>
<thead>
<tr>
<th>NB</th>
<th>From-To</th>
<th>Distance (miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>102-106</td>
<td>1.18</td>
</tr>
<tr>
<td></td>
<td>102-34</td>
<td>14.95</td>
</tr>
</tbody>
</table>

Table 4.8: Distances between origin and destination pairs for Northbound travel
Table 4.9: Distances between origin and destination pairs for Southbound travel

<table>
<thead>
<tr>
<th>From-To</th>
<th>Distance (miles)</th>
</tr>
</thead>
<tbody>
<tr>
<td>106-102</td>
<td>0.96</td>
</tr>
<tr>
<td>34-102</td>
<td>14.71</td>
</tr>
</tbody>
</table>

To examine the accuracy of these travel time estimates, they can be compared to actual travel times experienced by a GPS probe vehicle. Figure 4.14 shows the trajectories of a virtual vehicle and GPS probe vehicle both starting at the same time. It can be seen that the two trajectories are close and follow a similar pattern, though some differences are evident. Most notably, at mile 2.18, the probe vehicle slows more than the loop estimate. Such differences are due to the long sample period at the loops (5 minutes) and the fact that the loop data are aggregated across all lanes while the probe vehicle only occupies a single lane.

Extending this comparison, travel times from the loop detector data are estimated corresponding to the GPS probe vehicle start times for many days (33 for Northbound and 37 for Southbound). Figures 4.15 and 4.16 show the plots of estimated and observed travel times for Northbound and Southbound travel, respectively, for various origin and destination pairs. It can be observed that majority of the differences between travel times are less than 5 minutes even if traveling from one end (station 102) to the other end (station 34) of the freeway passing through the central business district. Even Washington Department of Transportation, which implements similar methodology to predict travel times in real-time, reports errors in a similar range [34].

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Figure 4.11: Mean of travel time as a function of time of day for the weekdays of August 2002, NB (A) with occupancy filter and correction factors (B) without occupancy filter and correction factors.
Figure 4.12: Mean and median of travel time as a function of time of day for the weekdays of August 2003, Northbound. (A) origin on I-70 and destination on I-71, just after the I-70/71 split (B) from one end to the other end of freeway passing through the central business district.
Figure 4.13: Mean and median of travel time as a function of time of day for the weekdays of August 2003, Southbound. (A) origin on I-71, just after the I-70/71 split and destination on I-70 (B) from one end to the other end of freeway passing through the central business district.
Figure 4.14: Comparison of a trajectory of a virtual vehicle estimated from loop detector data with the actual GPS probe vehicle’s trajectory. The starting times are same for both the vehicles.
Figure 4.15: Comparison of travel times estimated from loop detector data with GPS probe vehicle travel times, Northbound. (A) origin on I-70 and destination on I-71, just after the I-70/71 split (B) from one end to the other end of freeway passing through the central business district
Figure 4.16: Comparison of travel times estimated from loop detector data with GPS probe vehicle travel times for April 2003, Southbound. (A) origin on I-71, just after the I-70/71 split and destination on I-70 (B) from one end to the other end of freeway passing through the central business district.
Loop detectors are the most widely deployed traffic detectors on freeways. With the development of real-time traffic management applications such as incident detection, it is important to ensure that the quality of data from detectors is good. The first part of this thesis focused on developing validation tests to identify detector errors. Over the years, operating agencies have used threshold value tests to identify and eliminate erroneous aggregate data, thereby reducing the possibility of obtaining unexpected results. Such tests on aggregate data catch many errors. This thesis followed the event data approach to develop single loop as well as dual loop validation tests that catch even more detector errors. Though tests for both single loop and dual loop tests are developed, it was shown that applying single loop tests to each loop in a dual loop is sometimes beneficial. Tests that are fundamental to the working of a detector and should not be failed are identified with the idea of obtaining meaningful traffic parameters. Two types of thresholds were used, the first to check if an individual vehicle measurement is acceptable and the second to determine if the percentage of the acceptable data is greater than the minimum acceptable percentage for a given test. While the two types of thresholds are based on empirical evidence, a more
formal justification may be desired. It may be helpful to determine the impact of thresholds on aggregate traffic measurements, so that the thresholds for each test could be fine-tuned to meet the final data quality requirements, e.g., all the tests may not have the same threshold and the impacts of failing each test may affect the aggregate traffic parameters differently. Graphical color-coded plots are developed to visualize the test results and easily identify the detectors that do not perform well in each test. It was also shown that certain types of errors could be corrected using software routines, some of which include scaling errors in velocity and occupancy and removal of transient errors in velocity. Another problem that could be corrected for through software is pulse break-ups.

The next part of this thesis showed that single loop velocity estimation could be improved. Single loop velocity has been the focus of research for years, but little work has been done to estimate velocity from single loop data in presence of heavy truck flows. This thesis has shown the limitations of earlier velocity estimations in this situation and developed a methodology that addresses this problem without degrading performance under other traffic conditions. The results in Tables 4.3, 4.6 and 4.7 show that the new hybrid estimate is a significant improvement over conventional velocity estimates. This thesis has shown that cleaner data and better single loop velocity estimation methodology could lead to improved velocity estimates. To demonstrate the benefit of obtaining cleaner velocity, travel time is estimated using the cleaner velocity data and compared with actual GPS probe vehicle travel times to show their accuracy. The developed travel time profiles could be used to provide historical information to drivers and thereby gives the flexible drivers a chance to alter their travel plans to reduce their travel time and improve the travel conditions during congested periods of the day.
LIST OF REFERENCES


APPENDIX A

DATA PROCESSING

A.1 Pulse Matching

As detectors are not perfect, each detector in a dual loop pair detects different number of vehicles (the difference in the counts should be small unless one or both the detectors has severe problems). To calculate individual vehicle velocity at a dual loop, we need to match the upstream (u/s) loop and downstream (d/s) loop transitions. The following are a few ways to do this:

1) Create pulses when you don't see a matching pulse: In this method new pulses are created at either u/s or d/s loop depending on where you observe extra pulses. Of course, data are deleted when it appears to be due to detector errors. But for the new pulses, we need to come up with approximate start and end times for each new pulse created so that the data makes sense. Hence, this method is difficult to implement.

2) Match all extra d/s pulses to the last vehicle seen u/s: As the title suggests, all the extra d/s pulses are matched to the most recent u/s vehicle seen. Any extra pulses at the u/s loop are discarded.
3) Match all extra u/s vehicles to the immediate d/s vehicle: This method is just the opposite of the above method.

4) Delete all extra pulses: This method is simplest of all the methods described in this section. All the extra pulses are discarded. However, there is a possibility of losing lot of data in this case.

5) Correcting errors if possible: In this method, extra pulses are discarded only when continuous u/s and d/s errors are observed, i.e., delete the entire sequence of pulses if they are of the form u...uududd...d. Otherwise, the most recent pulse corresponding to the pulse at the other detector is retained and their on-times are made equal by adjusting the rising/falling edge of the retained pulse. Rising edge is adjusted when the retained pulse is at the u/s loop and falling edge if it is at the d/s loop. This method will be helpful when the loops experience flicker problems. Also, as the rising edges of some pulses are adjusted, errors in velocity are reduced.

Though there is no single “correct” method to match pulses, any one of the above could be used based on the purpose. For example, 2 and 3 could be used in data validation as explained in Chapter 3 of this thesis.

A.2 Summary data extraction

As the name indicates, Summary data summarizes a days’ data. The idea behind generating summary data is to be able to know if a day is “interesting” in the sense that it has congestion or incidents etc. so that it will be easy to pick data for research. We can also
know if data is not available for any of the stations or if the data is “bad”. The main tools that help in this regard are velocity summary plots generated for every month and the validation statistics for each day. The following are the data pulled out from a day of transition data.

1) Flow, Occupancy and Velocity by lane for all stations for two sample periods T=30sec and T=5 min.

2) Results of validation tests (both single loop and dual loop tests) by lane for all stations.

**Single loop:** Minimum and maximum Length tests, Percentage of vehicles with length over 25 ft, Percentage of vehicles with length over 50 ft, Mode On-time, Mode Off-time, Median On-time, Median Off-time, Over Maximum On-time, Under Minimum On-time, Under Minimum Off-time, Time Jumps, Number of negative transitions, Mode Correction factors, Number of Zero On-times, Number of Zero Off-times.

**Dual loop:** On-time difference, Moving median velocity difference test (using both rising edge and falling edge velocities), Minimum and maximum Length tests, Percentage of vehicles with length over 25 ft, Percentage of vehicles with length over 50 ft, Off-time difference test, Under Minimum Distance, Number of Vehicles, Number of free flow vehicles, Loop Correction factors.

In addition to the above tests, single loop tests are applied to each loop in a dual loop.

3) Delay, Vehicle Miles Traveled (VMT), Average Daily Traffic (ADT), hours of congestion and their plots. Delay for a sample period is defined as the difference in
travel times calculated using assumed free flow velocity and actual velocity of the sample period, multiplied by the number of vehicles observed in that sample period. Both delay by station and time are calculated. VMT for a sample period is calculated by multiplying the vehicle count of that sample with the corresponding link distance assigned for the station under consideration. Again, VMT by station and time are calculated. ADT is the number of vehicle seen at a station. Figures A.1-A.4 show the plots of all the above-mentioned parameters.
Figure A.1: Sample delay plot for I-71 (A) by station (B) by time of day
Figure A.2: Sample flow plot for I-71 (A) by station (B) by time of day
Figure A.3: Sample congestion measure plot for I-71 (A) by station (B) by time of day
Figure A.4: Sample VMT plot for I-71 (A) by station (B) by time of day
A.2.1 Velocity summary plots

Color-coded plot of velocity represented in time-space plane could be helpful in understanding the performance of a freeway. Such plot highlights congestion and congestion due to incidents or recurring bottlenecks could be easily identified by observing such plots for several days. Two types of velocity summary plots are generated, the first is a plot of 5 min aggregated velocities for all stations, shown in Figure A.5, and the second is a plot of difference in velocities between mean day and current day, shown in Figure A.6. The difference plot particularly highlights the congestion due to unexpected events such as incidents that do not occur regularly. Both the plots are oriented such that traffic is moving from bottom to top. Also, horizontal lines are drawn at locations where I-670 and I-270 intersect I-71, for reference. Figures A.7 shows a sample summary plot for a month of data. The plot is arranged in the layout of month with mean for each week and each weekday plotted in the last column and row of figures respectively. Only weekdays are considered to plot mean for a week as most of the weekend we observe free flow conditions. Figure A.8 shows a sample difference plot for a month of data. Mean day for both weekdays and weekends in a month are calculated and used accordingly to calculate difference between mean day and current day based on whether the current day is a weekday or weekend.
Figure A.5: Sample velocity summary plot for I-71 for a day of data

Figure A.6: Sample velocity difference summary plot for I-71 for a day of data
Figure A.7: Sample velocity summary plot for I-71
Figure A.8: Sample velocity difference summary plot for I-71
A.3 Visualization of validation test results for BHL data

As said in Chapter 3, it is sometimes difficult to look at a table of test results and identify problem detectors. To this end, color-coded plots were developed for I-71 and shown in Chapter 3. Similar plots were also developed for BHL data, but we have only 9 detector stations and all are dual loops. Figures A.9-A.11 show the plots for single loop tests, dual loop tests and results by lane respectively.
Figure A.9: Sample color-coded plot to visualize single loop test results for BHL data
Figure A.10: Sample color-coded plot to visualize dual loop test results for BHL data
Figure A.11: Sample color-coded plot to visualize validation test results by lane for BHL data