AUTOMATIC SYSTEM TO MEASURE TURNING MOVEMENT AND

INTERSECTION DELAY

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AUTOMATIC SYSTEM TO MEASURE TURNING MOVEMENT AND

INTERSECTION DELAY

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Thesis

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ABSTRACT

It is important for many traffic operations, such as real-time adaptive signal control, dynamic traffic assignment and traffic demand estimation, to obtain the vehicle turning movement information at a signalized intersection. However, it is laborious and time consuming to count the turning movements manually. Previous efforts on this problem relied on a mathematical approach by solving an O-D matrix in which the turning movements represent distributions of the arriving flow at each intersection approach. However, such a matrix cannot be mathematically solved without using supplementary volume data from the local detectors; previous studies showed the results from the O-D method are not accurate. Identifying vehicle turning movements from detector information is a more direct method. Limited studies using this method have been found for intersections without shared lanes. Most intersections allow shared lane operations, thus this method is not practical without further improvements. Driven by the need to identify vehicle turning movement automatically regardless of the geometry and operation of the intersection, this research studied and developed a system called Automatic Turning Movement Identification System (ATMIS). ATMIS utilizes intelligent detection matching algorithm to identify vehicle turning movements from the detections collected from the field in real-time. This algorithm has the capability to compensate the error caused by the faults detections and shared lanes. The results from laboratory experiments and field tests are very encouraging. Future work is also discussed in the thesis.

While another related study, intersection delay measurement, is also included in this thesis. Delay is regarded as one of the most important Measures of Effectiveness (MOE) for signalized intersections. Different methods to measure control delay are recommended by many researchers but most of them are costly, time consuming and labor intensive. Some key components of delay measurement, such as intersection delay and delay for different turning movements, are not addressed in the previous studies. Driven by the need to develop an automatic delay estimation system, a method is presented to improve or extend the current methods to estimate intersection travel time based on the detection information derived from ATMIS. Yet, the detection information is not perfect from ATMIS, we still can estimate intersection delay accurately with the help of data filters. The mechanism and result of proposed method are discussed in this thesis. Further work of delay measurement is also presented.

ACKNOWLEDGEMENTS

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The helpful advices, operation interface and algorithm programming and collaboration from Chun Shao who was a Ph.D. candidate of Professor Ping Yi at Civil Engineering in the University of Akron are gratefully acknowledged. The useful videos derived from the city of Akron are really appreciated. Acknowledgments are also extended to my committee members Dr. William H Schneider IV and Dr. Anil Patnaik, for reviewing my work and helpful recommendations.

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CHAPTER I

INTRODUCTION

1.1 Motivation and General Description

Turning Movements Information (TMI) for vehicles at signalized intersection is important for many traffic operations including but not limited to adaptive signal control, dynamic traffic assignment and traffic demand estimation. Traditionally, TMI is collected manually with handheld devices in the field which makes it a tedious, labor intensive and time-consuming job (1). The requests of real-time TMI data from applications like adaptive signal control encouraged the exploring in obtaining vehicle turning movements automatically. Previous efforts on this problem mainly focused on a mathematical method by solving an O-D matrix in which the turning movements represent distributions of the arriving flow at each intersection approach. However, such a matrix cannot be mathematically solved without using supplementary volume data from local detectors; previous studies showed the results from the O-D method are not accurate. Identifying vehicle turning movements from detector information is a more direct method. Limited studies using this method have been found for intersections without shared lanes. Since many intersections in the field allow shared lane assignments, this method is not practical without further improvements. Driven by the need to identify vehicle turning movement automatically regardless of the geometry and operation of the intersection, this research studied and developed a system called Automatic Turning Movement Identification System (ATMIS). With the help of advanced detection technology and intelligent detection matching algorithm, ATMIS can provide accurate TMI data in real-time regardless of the geometric layout of the intersection.

The development of ATMIS has provided a solid foundation for other researches including vehicle delay estimation. Average vehicle delay for each turning movement is considered as one of the most important Measures of Effectiveness (MOE) for the performance of intersection operation. Field delay measurements are valuable but can be costly, because they require extensive human judgment and intensive data collection. With the advance in Intelligent Transportation System and the public concern regarding congestion costs, existing methods cannot meet the demand of convenient and accurate performance measurement. In this thesis, an ATMIS based delay measurement method has been proposed and discussed. This method will estimate the intersection delay for individual vehicles based on the information obtained from ATMIS. Data filters were used to improve the accuracy of the estimation and the laboratory tests have shown the promised results of this method.

1.2 Thesis Contents and Organization

A literature review, which examines the histories and limitations of the researches in identifying vehicle turning movements and vehicle delay estimation, is presented in Chapter II. Chapter III illustrates the model of ATMIS and discusses the detail of its algorithm. The results of laboratory and field experiments along with the analysis of errors are presented in Chapter IV. After that, the application of ATMIS in vehicle delay estimation is demonstrated in Chapter V. The methodology used in the estimation and the results of the experiments are discussed in detail. Finally, the summary of this research and future works are presented in Chapter VI.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature related to the vehicle turning movement identification and vehicle delay estimations. The methodologies used in previous research are introduced briefly and their limitations are addressed as the motivation for the developing of ATMIS. Terminologies and concepts used in this research are also defined in this chapter.

2.2 Vehicle Turning Movements Identification

The importance of TMI for vehicles at signalized intersection has been revealed since 1981 (8). Beside traffic routine decision applications, the information can be applied in dynamic traffic assignment, adaptive signal control, and transportation planning. Many studies have been done in obtaining TMI either through mathematical approach or directly from detection data. Their contributions and limitations will be addressed in the following sections.

2.2.1 Mathematical Approaches

With the improvement in vehicle detection system, origin-destination (O-D) matrix method was first introduced into TMI in 1981 by Cremer and Keller (8). Consider a signalized intersection as presented in Figure 2.1, where detectors are placed on each lane to detect both arriving and leaving vehicles. Suppose the traffic volume flow into/out of the intersection on each leg is known for given time period t, with the assumption that no vehicle exists in the system before and after the time period t, we can have the following equations:

$$\begin{pmatrix} 0 & b_{21} & \cdots & b_{N1} \\ b_{12} & 0 & & b_{N2} \\ \vdots & & \ddots & \vdots \\ b_{1N} & b_{2N} & \cdots & 0 \end{pmatrix} \begin{pmatrix} I_1 \\ I_2 \\ \vdots \\ I_N \end{pmatrix} = \begin{pmatrix} O_1 \\ O_2 \\ \vdots \\ O_N \end{pmatrix} \qquad 2.1$$

Where,

N	the number of legs for the studied intersection
I_i	traffic volume going into the intersection at leg i (i = 1 to N)
O_j	traffic volume going out of the intersection at leg j (j = 1 to N)
b_{ij}	probability for a vehicle entering the intersection from leg i will leave at leg j (i = 1 to N and j = 1 to N)

According to the definitions, we can have the following constraints in addition:

$$\begin{cases} b_{ij} \geq 0 \text{ when } i \neq j \\ b_{ij} = 0 \text{ when } i = j \end{cases} \quad \text{where } i, j = 1 \text{ to } N \qquad 2.2$$

With the assumption that no U-Turn is allowed, we can get

$$\sum_{j=1}^{N} b_{ij} = 1 \text{ where } i = 1 \text{ to } N \qquad 2.3$$

Once the O-D matrix composed by b_{ij} has been solved, the volume of vehicle turning movements can be calculated by multiplying the probability b_{ij} with corresponding volume q_i.

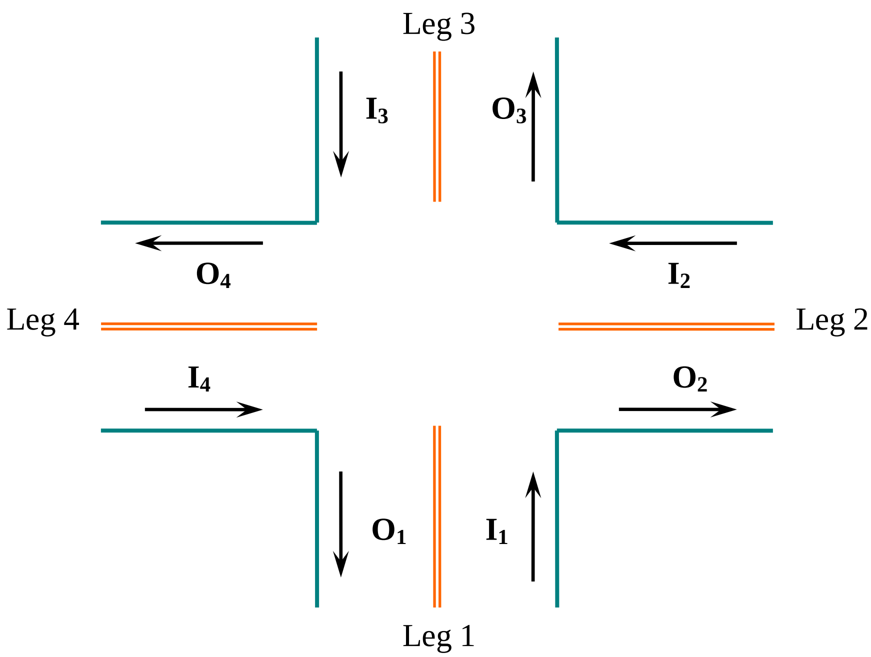


Figure 2.1 Basic Intersection Model

However, this seemingly simple mathematical problem cannot be easily solved. It has been found that when the number of legs is more than 3, the matrix has multiple solutions due to more variables than equations. In addition, the mathematical formulation requires that there be no errors in the traffic volume data at each leg; otherwise, it will become an unsolvable matrix. To address these problems, plausible assumptions need to be applied or additional constraints must be provided. This limits the potential of this model for field applications. Nihan and Davis (9) developed a Kalman filtering algorithm to solve the O-D matrix. It is an extension to stochastic gradient algorithm in dynamic identification of flow distributions at complex intersection. However, this method is not reliable, as the Root Mean Square (RMS) error is from 29.2% to 49.4%. Later Cremer and Keller (10) proposed an application of maximum likelihood algorithm for intersection O-D matrix estimation. Similarly, the RMS error of their model is from 6.1% to 24.7%.

Furthermore, all the above models rely on rigid assumptions and accurate volume information. In practice, the error from human operation and detection facilities in traffic volume counting is hard to be eliminated. To compensate the error in traffic volume, Jiao, Lu and Yang (11) developed a method using Genetic Algorithm to identify TMI in 2005. Yet, the simulation result of this method is encouraging with the turning movements identification ratio is around 98%, the detection error is about only 5% in the simulation, which could be much higher in the field according to our research.

Finally, in order to minimize the affection from the fluctuation of the traffic flow and obtain better results, the studied time period t is relatively long (more than 15 minutes) in O-D matrix method. It prevents the application in adaptive signal control since the resolution of vehicle turning movements is not fine enough.

2.2.2 Detector Data Processing

Another approach to identifying TM is to make use of the detector data directly. In 1998, Time And Place System (TAPS) was first developed by Virkler and Kumar (12) in University of Missouri-Columbia and five more field tests were conducted in 2004 (13). In TAPS, phasing and detection information are utilized to identify vehicle turning movements at signalized intersection in real-time. In the field tests, the average errors of turning movement identification under non shared lane scenario are from 8% to 16% while it increased to 13% to 36% when shared lane exists. Especially, the shared left turn movement can yield as high as 71% error compared with 10% error in shared right turn in the same test. This is because a special detector is placed at the corner of the intersection to help detect right turn vehicles at shared lane while this method cannot be applied with shared left turn. Another effort on identifying TMI is from Texas Transportation Institute performed by Sunkari, Charara and Urbanik in 2000 (14). They introduced a similar method to TAPS to estimate vehicle turning movements at a signalized diamond interchange. Their method also requires special right turn detectors and no shared left turning lane exists during the test. According to their limited experiment result (only one scenario is tested), the turning movement identification error is about 10% in average.

For the above methods, identification of left turn vehicles at shared lane is never addressed. The accuracy of turning movement identification relies on the special right turning detector whose result is affected by its position and the influence from other vehicle movements such as left turn in the opposite direction and through vehicles from the side street.

2.3 Delay Measurement

According to HCM 2000, control delay is defined as the additional travel time experienced by a vehicle affected by intersection control. As shown in Figure 2.2, control delay can be separated into different sections such as deceleration delay, stop delay, acceleration delay, approach delay and intersection delay. Their definitions are listed as follows:

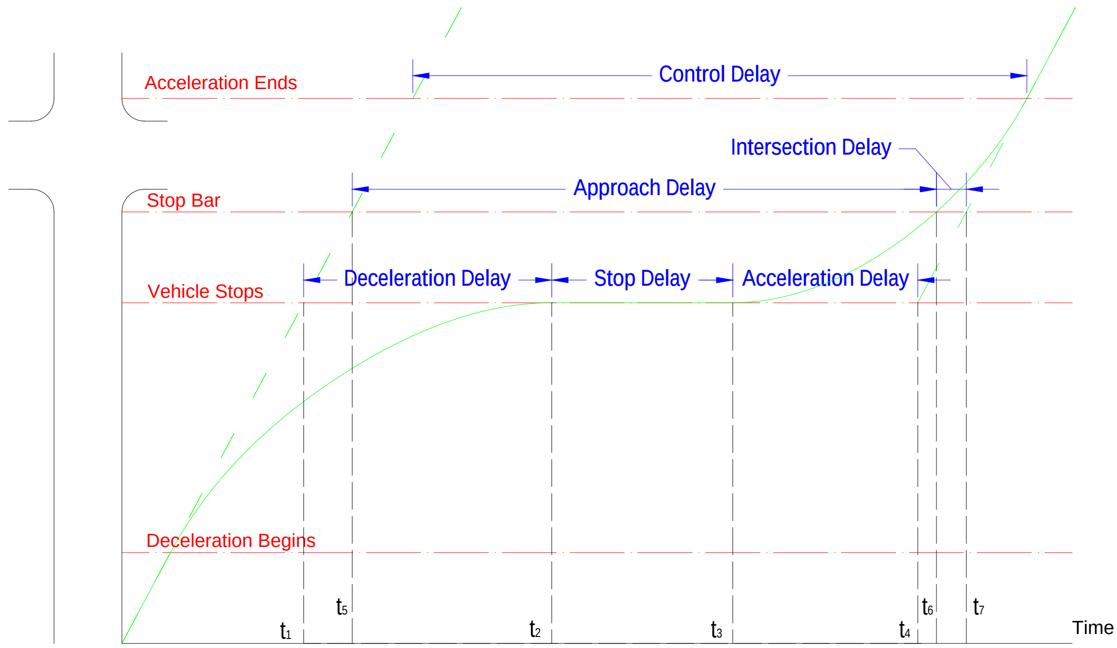


Figure 2.2 Different Types of Vehicle Delay

• Control delay is the total delay experienced by a vehicle due to intersection control *(2)*.

• Approach delay is the delay experienced by a vehicle before entering the intersection.

• Intersection delay is the additional travel time experienced by a vehicle after it entered the intersection and before it reaches free-flow speed.

• Deceleration delay is defined as the delay experienced by a vehicle when it is reducing its speed.

• Stop delay is the waiting time of a vehicle when its speed is zero (in practice we consider the vehicle is stopped when its speed is less than 5 mph) *(1)*.

• Acceleration delay is defined as additional travel time experienced by a vehicle due to the acceleration period.

According to the definitions, we can find the following relationship among different vehicle delays:

Control Delay = Deceleration Delay + Stop Delay + Acceleration Delay 2.4

Control Delay = Approach Delay + Intersection Delay 2.5

Kinzel (3) suggested a method in Traffic Engineering Handbook to measure vehicle delay in the field based on sampling the number of vehicles in queue at signalized intersection. This method does not directly measure control delay but stop delay and uses adjust factors to estimate control delay. Later in HCM 2000, similar method is recommended. The accuracy of this method is highly relied on the adjust factors and it is very labor intensive to collect data at multi-lane intersection.

Another method developed by Quiroga, C. A., and Bullock, D. tried to use Global Positioning System (GPS) to estimate control delay (2). It records the location and speed of sampling vehicles every second. However the sample size (vehicles with GPS system) has limited the accuracy of this method.

Mousa, R. M (4) suggested a method for measuring and analyzing control delay by tracking vehicles' arrival time at check points manually. In the field experiment, twelve screen lines (check points) were marked for one approach with 27 to 55 meters gap between each line. People are required to record the crossing time for each vehicle at the screen line with audio-cassette recorders. Again, this method is very labor intensive and it is difficult to track vehicles when the volume is high.

The photographic technique is also suggested by the committee on operating speeds in urban areas at 1955 (5). By continuously taking photos of intersection approaches, vehicle delay can be calculated manually. However, this method is very labor intensive and not recommended to be used for comprehensive studies.

Teply (6) suggested a method to measure approach delay in the field using three timestamps: the arrival time of vehicles over a point that is located upstream of the approach beyond the queue point that the usual could reach; the time vehicle across the stop bar; and the beginning and the end of green phase. This method is more amenable to accurate field implementation than sampling techniques that require more complex data collection judgment. However, it doesn't address the intersection and the delay for different turning movements is not separated. Further study by Wassim (7) recommended setting more detectors in approach to cover all turning lanes. In this case, the approach delay for different turning movements can be obtained separately.

In short, most of the above methods are operating manually and the accuracy of the control delay cannot be satisfied. Though Teply and Wassim's method can yield promised results and has the potential to be applied automatically, the intersection delay is not measured and the delay for different turning movements under shared lane condition is not separated. Driven by the need to obtain reliable control delay for each turning movement at signalized intersection automatically, we proposed a detection based method from the data provided by ATMIS to measure intersection delay for all turning movements.

CHAPTER III

METHODOLOGY OF ATMIS

3.1 Introduction

Identifying vehicle turning movement automatically at shared lane intersection is always a challenge to transportation engineers. Driven by the need for developing an automatic system to identify vehicle turning movements regardless of the geometry layout of the signalized intersection, we developed ATMIS in transportation laboratory at The University of Akron. This system is independent to the geometric layout of the intersection, such as shared lane and irregular intersection (more than four legs or odd shape), and tolerant to detection errors. Video detection unit is recommended in ATMIS according to its low cost and convenience to place detectors. In the following part, we will discuss the algorithm used in ATMIS.

3.2 ATMIS Algorithm

The algorithm used in ATMIS is based on detector system and signal information. By tracking each detector's status and traffic signal code second by second, vehicle turning movement can be calculated in real-time. To illustrate this algorithm, we will take a four-leg intersection as an example. The detector configuration for a typical four-leg one-lane intersection is shown in Figure 3.1. The white detectors are placed close to the stop bar at each flowing in lane to detect vehicles arrival at the intersection; the gray detectors are placed at each flowing out lane to detect vehicles leaving the intersection. No matter when there is a vehicle pass the intersection, a pair of detections from arrival detector (white) and leaving detector (gray) will be raised. For different pairs of detectors, we have different corresponding turning movements as shown in Table 3.1. The algorithm in ATMIS will use this table along with the detection information and signal status to identify vehicle turning movements.

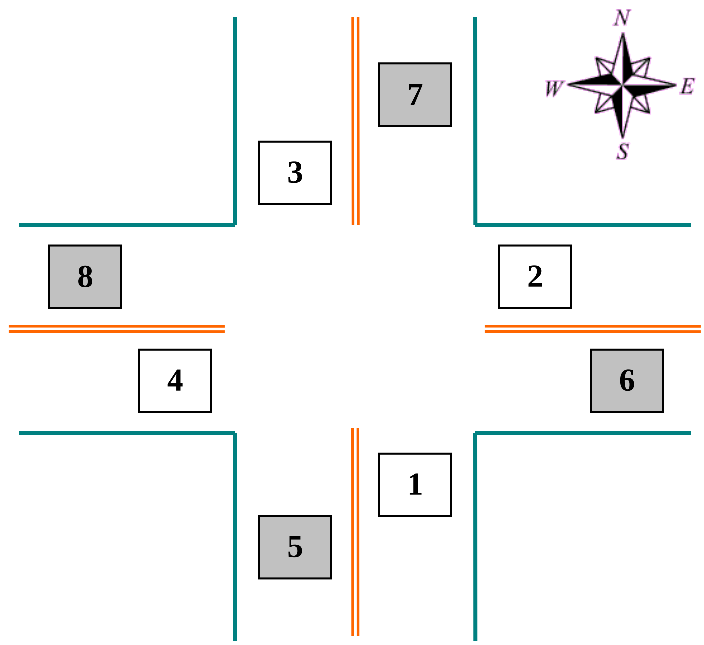


Figure 3.1 Detector Configuration for a Four-Leg One-Lane Intersection

At signalized intersection, only part of the vehicles approaching the intersection can get the right of way at one moment. The signal information can help us to narrow the candidate movements. However, the process to identify turning movements from detector pair can still be very complicated when there are multiple choices caused by shared lane.

For instance, detection from detector 6 can be paired with detection from detector 1 and get northbound right turn or it can get southbound left turn when combined with detection from detector 3. The purpose of our algorithm is to identify the turning movement under such complicated circumstance and independent to the geometry of the intersection. There are three modules in our algorithm, Input Detection Recording Module, Output Detection Matching Module and Input Detection Cleanup Module. As shown in Figure 3.2, the detail procedures of these three modules are introduced below.

Table 3.1 Corresponding Turning Movement for Detector Pair

Arrival Detector	**Leave Detector**	**Turning Movement**	**Abbreviation**
1	7	Northbound Through	NBT
1	6	Northbound Right Turn	NBR
1	8	Northbound Left Turn	NBL
2	8	Westbound Through	WBT
2	7	Westbound Right Turn	WBR
2	5	Westbound Left Turn	WBL
3	5	Southbound Through	SBT
3	8	Southbound Right Turn	SBR
3	6	Southbound Left Turn	SBL
4	6	Eastbound Through	EBT
4	5	Eastbound Right Turn	EBR
4	7	Eastbound Left Turn	EBL

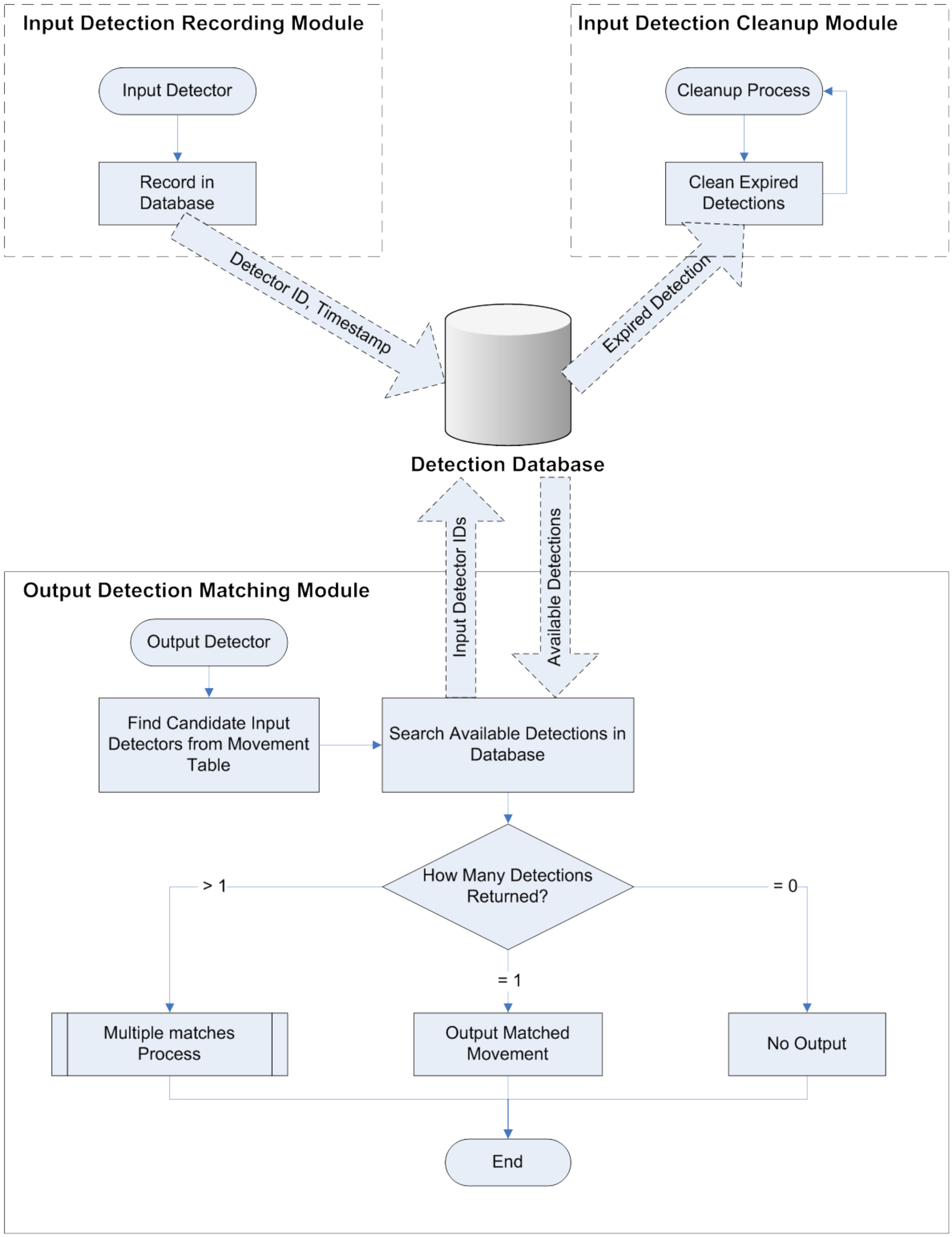


Figure 3.2 Flow Chart of ATMIS Algorithm

3.2.1 Input Detection Recording Module

This module is triggered by the detection from input detectors. Once the status of an input detector changes from activation to deactivation, which means the vehicle occupied the detector has left; the detector's ID and the deactivation timestamp will be recorded and sent to the database. The timestamp will be used in two places, the first is to match the sequence in detector pair and the second is to time-out unmatched detections. These input detections will be used later in the other two modules.

3.2.2 Output Detection Matching Module

This module is triggered by the detection from output detectors. An output detection means there is a vehicle left the intersection and there should be one and only one input detection matched with it. However, in practice, it will not always just return one matched input detection from the database. As shown in Figure 3.2, there are three possible cases described as follows.

Case I: There is no matched detection in the database.

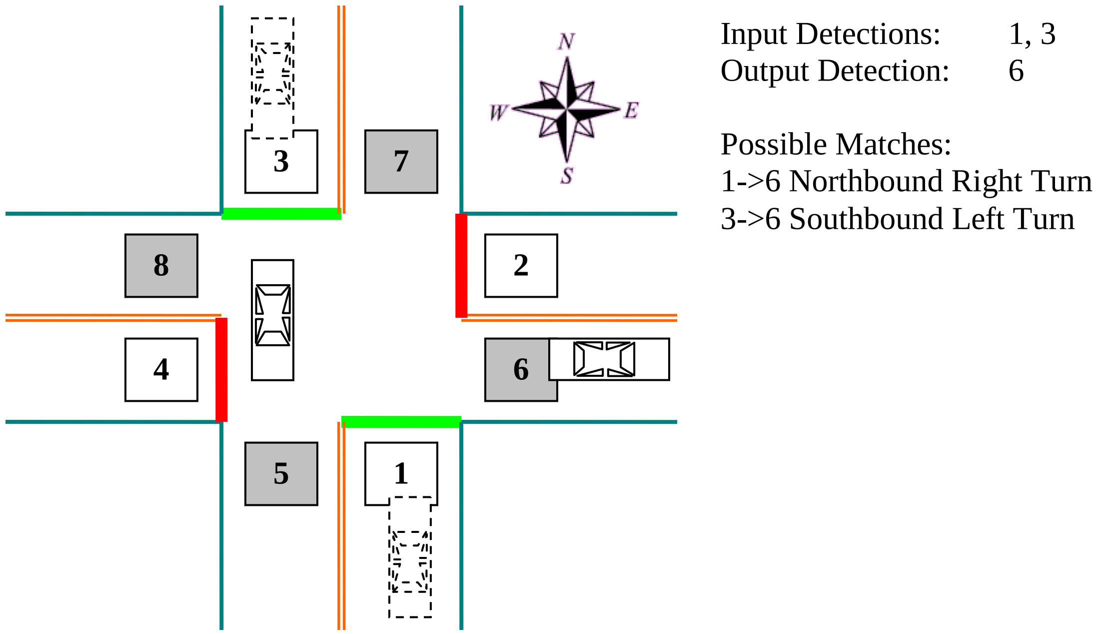
No matched detection can be caused by either miss detection on input detectors or false detection from output detectors. Since any detection in the future will not be helpful to solve this problem, we will just ignore the output detection in our algorithm and output the error.

Case II: There is only one matched detection in the database.

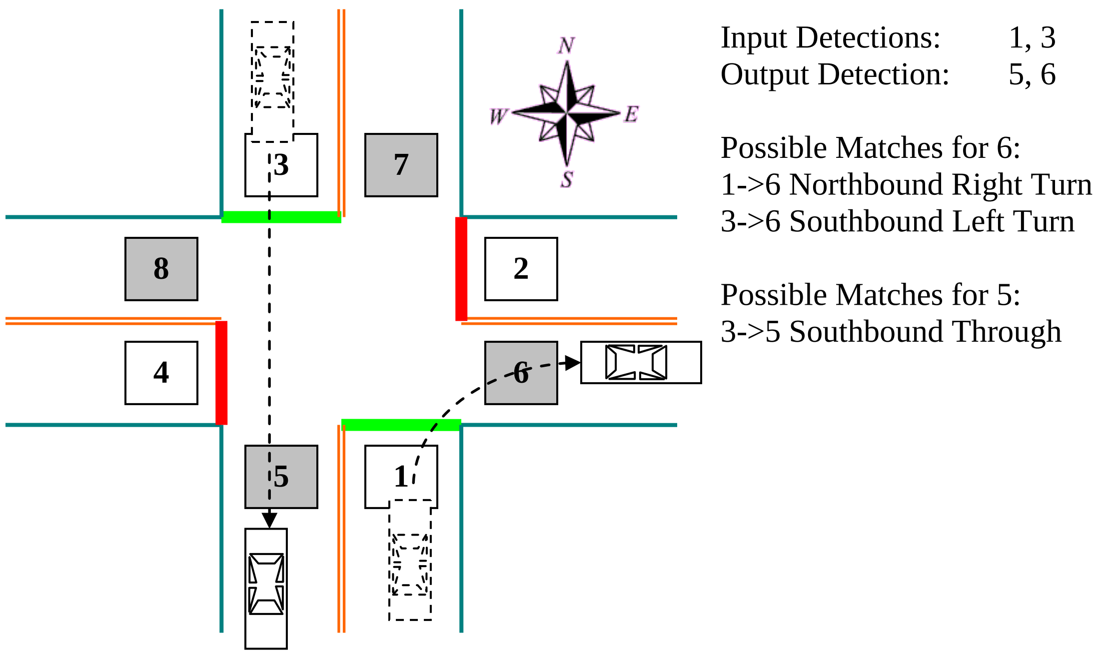
This is the best condition for detection match. We will simply search the turning movement table and find out the corresponding movement for the detection pair from the turning movement table. The corresponding output and the input detection will be removed from the database.

Case III: There are more than one matched detection in the database.

This is the most complicated situation we will meet in the algorithm. It can be caused by many reasons, such as false detections, vehicles not cleared in the intersection and etc. The process to solve this problem is very complicated and introducing the detail of it is out of the scope of this thesis. We will try to explain the basic idea of this process by a simple case shown as follows. Think about a four-leg intersection with one lane on each direction as shown in Figure 3.3 There is a vehicle moving from south to east (northbound right turn) and another vehicle moving from north to south (southbound through). At one moment, the vehicles' position is shown in Figure 3.3. There are two input detections saved in database which is detector 1 and detector 3. When the vehicle leaves detector 6, one output detection will be sent to the system. The algorithm will pull out the possible input detections from the database, which are detections from detector 1 and detector 3. It is hard to tell which one is correct and the algorithm will hold all the detections and not output anything at that moment. The multiple matches will be broken when the southbound vehicle leaves the intersection. As shown in Figure 3.3 (b), we have two output detections now; one is from detector 5 and the other is from detector 6. Though there are still two possible matches for output detection 6, there is only one input detection (from detector 3) matches with output detection 5. The algorithm will output the movement southbound through and remove the input detection 3 from the database. Consequently, we only have one input detection (from detector 1) matches with output detection 6. The algorithm will output northbound right turn and remove the input detection 1 from the database. Thus, all the output detections have been matched and the turning movements are revealed.



(a) Unsolvable Situation Caused by Vehicle not Cleared



(b) Solvable Situation when Vehicle Cleared the Intersection

Figure 3.3 Example of Process Multiple Matched Input Detections

In practice, it could be much more complex situation than this case, and the algorithm is designed to handle all the possibilities.

3.2.3 Input Detection Cleanup Module

This module is an independent process which cleans up the expired input detections. Input detections which have no matched output detection for a given time should be removed from the database. These non-matched detections may be caused by false detection from input detector or miss detection on output detector. The expiration time is preset by the system (usually the length of phase in experience) and the cleanup process is performed every second. This module is very important to break the multiple matches' situation in the algorithm.

CHAPTER IV

ATMIS EXPERIMENTS AND RESULTS

4.1 Laboratory Experiments

After the algorithm has been developed, ATMIS was tested in the laboratory first with prerecorded video from the field. The system architecture and test results are discussed below.

4.1.1 System Architecture

ATMIS is built based on NEMA standard system and consists of two parts, hardware and software. The hardware used in laboratory experiments includes a DVD player, RCA cables, video amplifier, video detection unit (such as Autoscope® 2020), R485 Cable, interface card and a personal computer as shown in Figure 4.1. The DVD player simulates the cameras to provide continuous video for detection system. The videos played in DVD player are prerecorded in the field with 4-in-1 to keep the synchronization of four cameras as shown in Figure 4.2. Since one DVD player needs to supply four video detection units (simulate four cameras at one time), a video amplifier is necessary to compensate the weakened signal due to splitting. The detectors are configured in the video detection unit according to the video provided by DVD player.

This unit is connected to a personal computer equipped with an interface card through R485 cable. The software of ATMIS is installed in this computer.

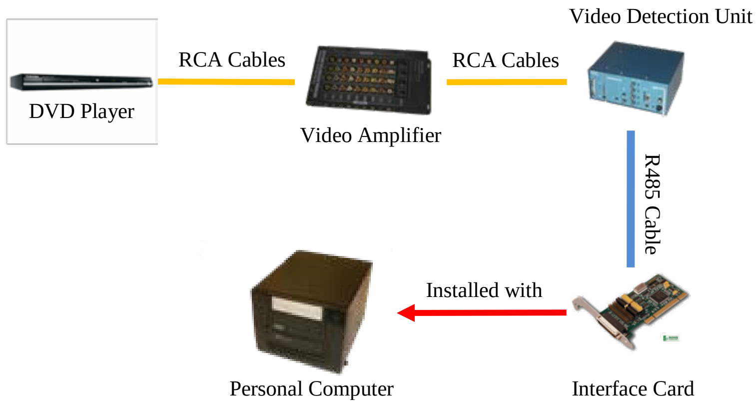


Figure 4.1 ATMIS Architecture

Figure 4.2 Prerecorded Video for Laboratory Experiment

The software part of ATMIS includes a NEMA standard traffic controller emulator and vehicle turning movement identification program. The controller emulator simulates a NEMA standard traffic controller to send out messages (frames) to detection unit and receive detection information (frames). The interface of emulator is shown in Figure 4.3. Notice that the signal status has to be inputted manually according to the video during the test since the control logic of traffic controller is not emulated.

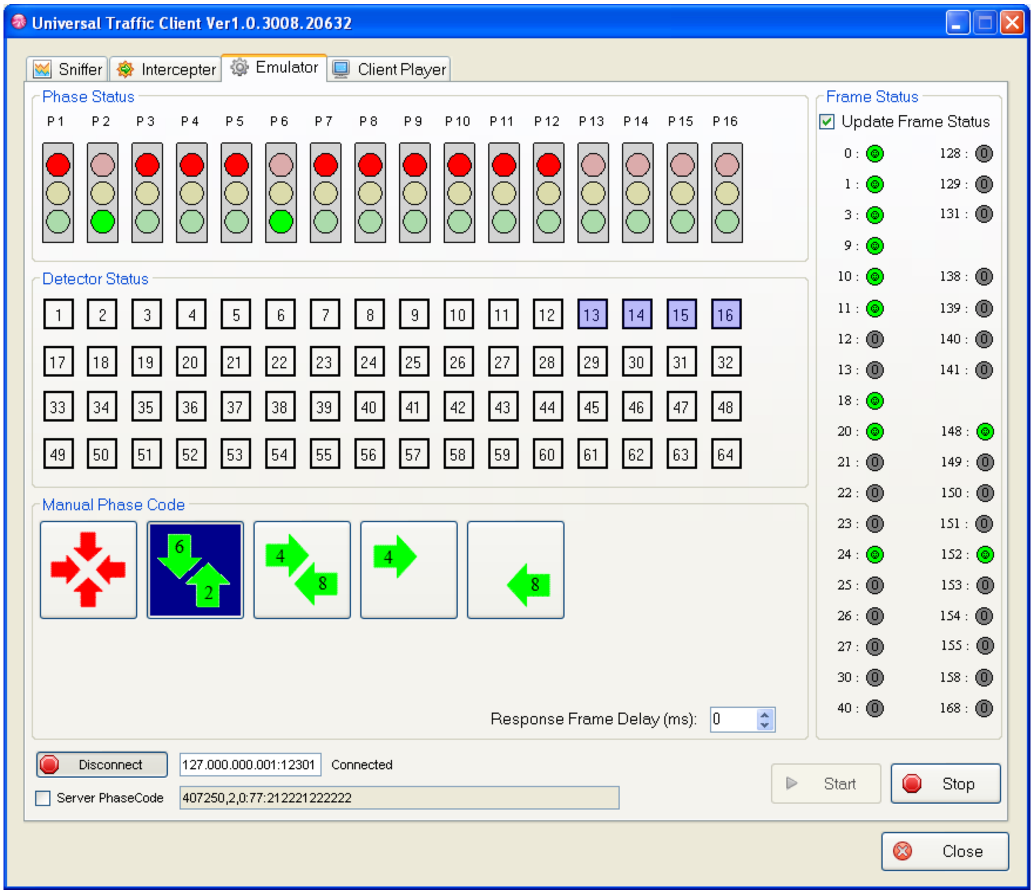


Figure 4.3 NEMA Standard Traffic Controller Emulator

Once the detection information is collected in controller emulator, it will be forwarded to vehicle turning movement identification program along with the signal status. The interface of identification program is shown in Figure 4.4. Vehicle turning movements are identified with the built algorithm based on the detections and signal status. The results can be exported to Microsoft Excel ® for further study.

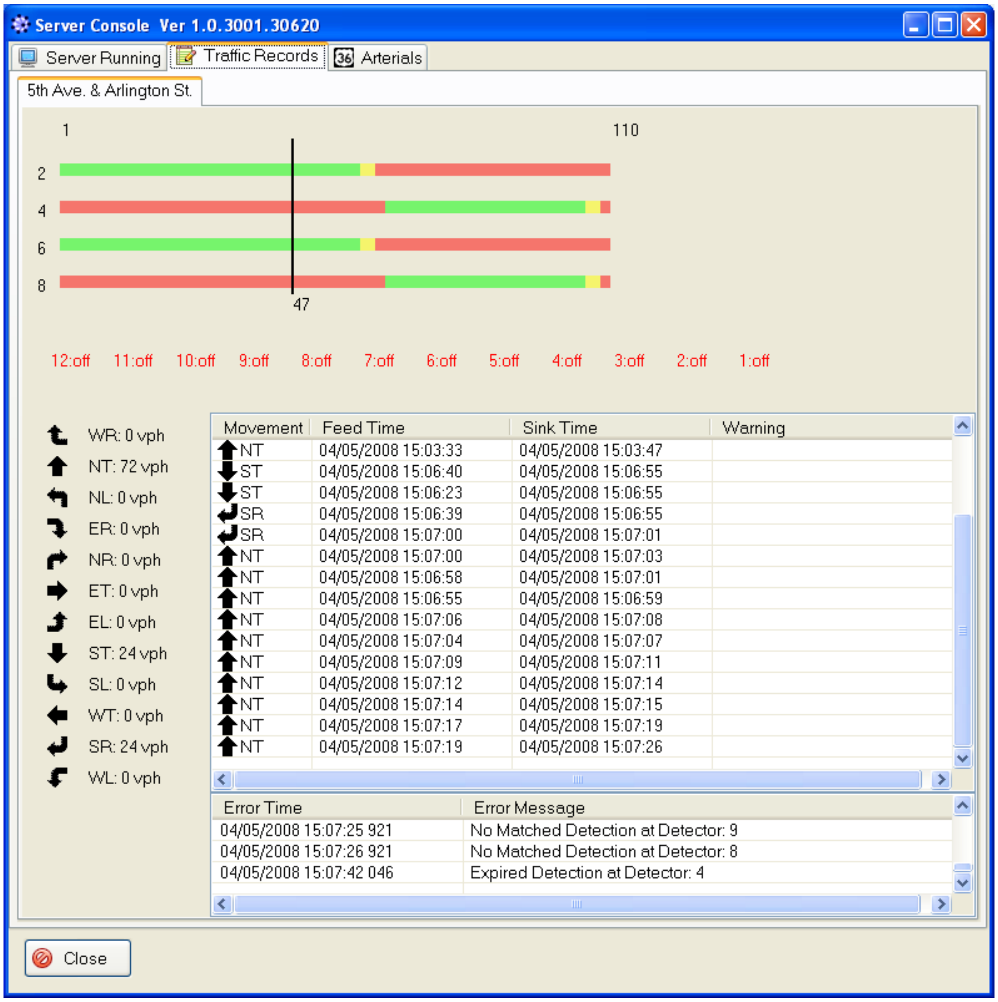
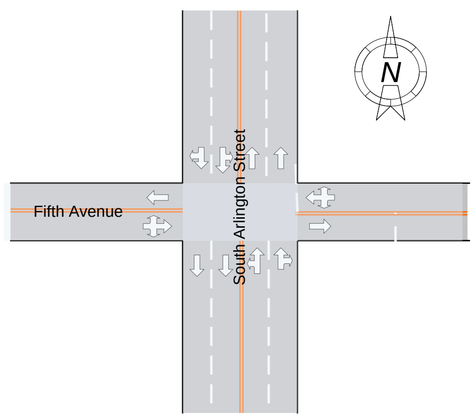


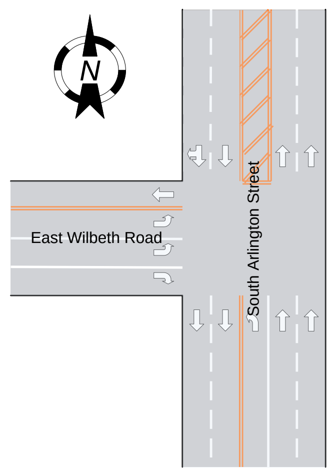
Figure 4.4 Turning Movement Identification Program

4.1.2 Experiments and Results

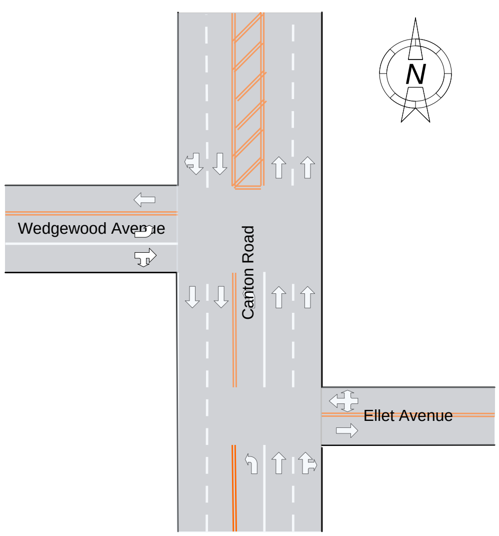
There are three intersections tested in laboratory experiments including intersection of Fifth Avenue at South Arlington Street, East Wilbeth Road at South Arlington Street, and Wedgewood Avenue at Canton Road. These three intersections are all video camera equipped and their geometries are different. As shown in Figure 4.5a, the intersection of Fifth Ave. and S. Arlington St. is a regular four-leg intersection with shared lanes. The intersection of E. Wilbeth Rd. and S. Arlington St. is a T-intersection with only one lane shared by right turn and through traffic. Most lanes in this intersection are excluded lanes as shown in Figure 4.5b. The third intersection, Wedgewood Ave. at Canton Rd., is an irregular intersection. From Figure 4.5c we can find that the two side street, Wedgewood Ave. and Ellet Ave. are shifted. The difference among these intersections demonstrates the ability of ATMIS to handle various intersections regardless of the geometry.



(a) Fifth Ave. and S. Arlington St.



(b) E. Wilbeth Rd. and S. Arlington



(c) Wedgewood Ave. and Canton Rd.

Figure 4.5 Geometry Layout of Three Intersections in Laboratory Experiments

For each intersection, a video tape is recorded during the day time. The duration of the video varies from 60 minutes to 100 minutes. The ground truth of the turning movements is collected with 20 minutes interval and the results of the experiments are shown in Figure 4.6, Figure 4.7 and Figure 4.8.

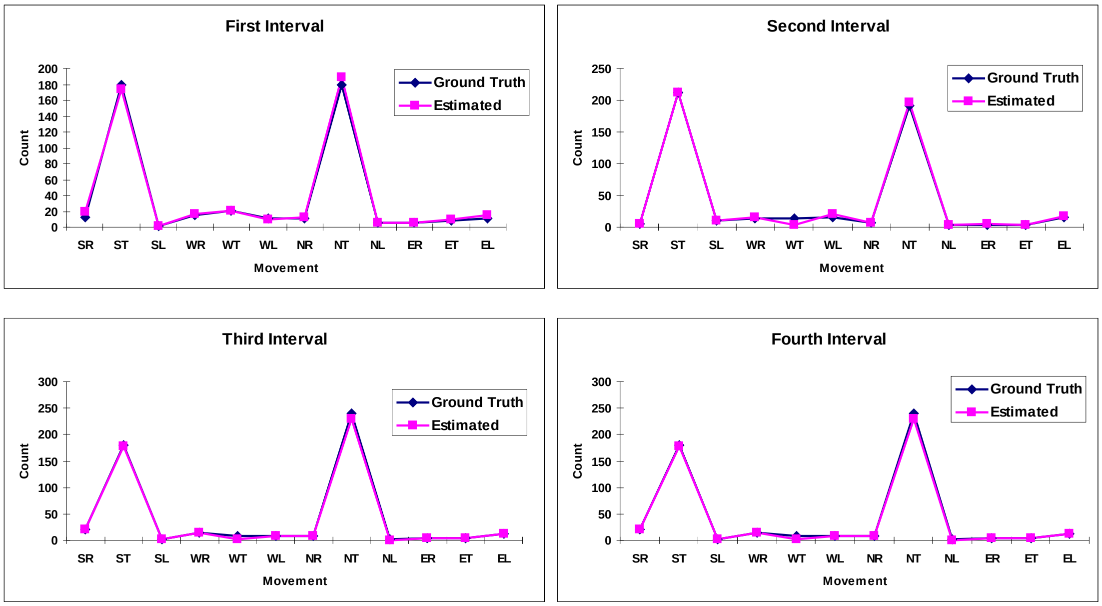


Figure 4.6 Laboratory Experiment Results on Fifth Avenue at South Arlington Street

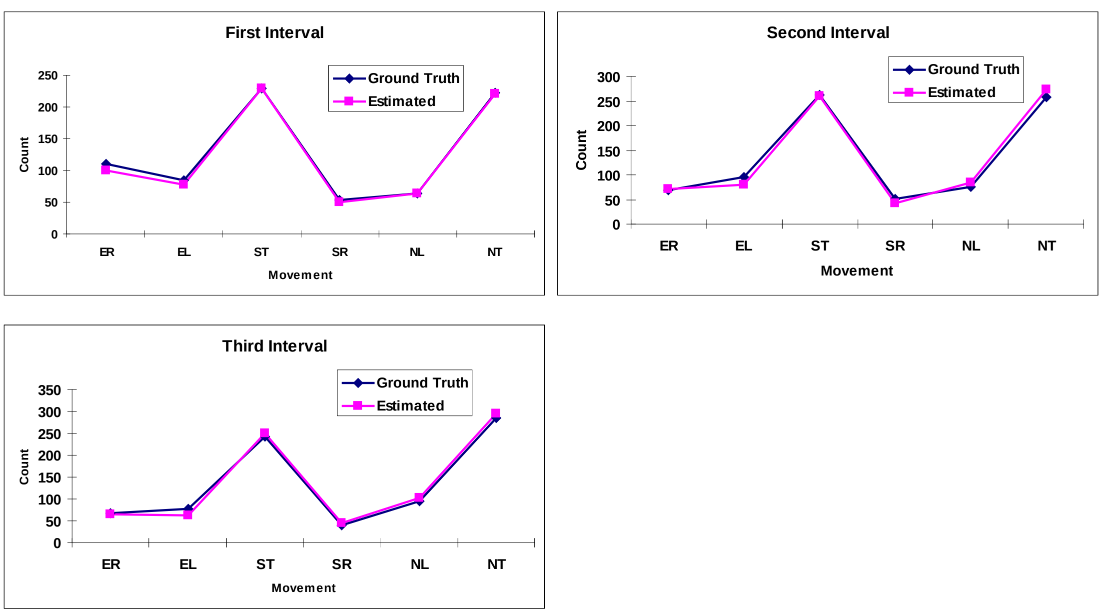


Figure 4.7 Laboratory Experiment Results on East Wilbeth Road at South Arlington Street

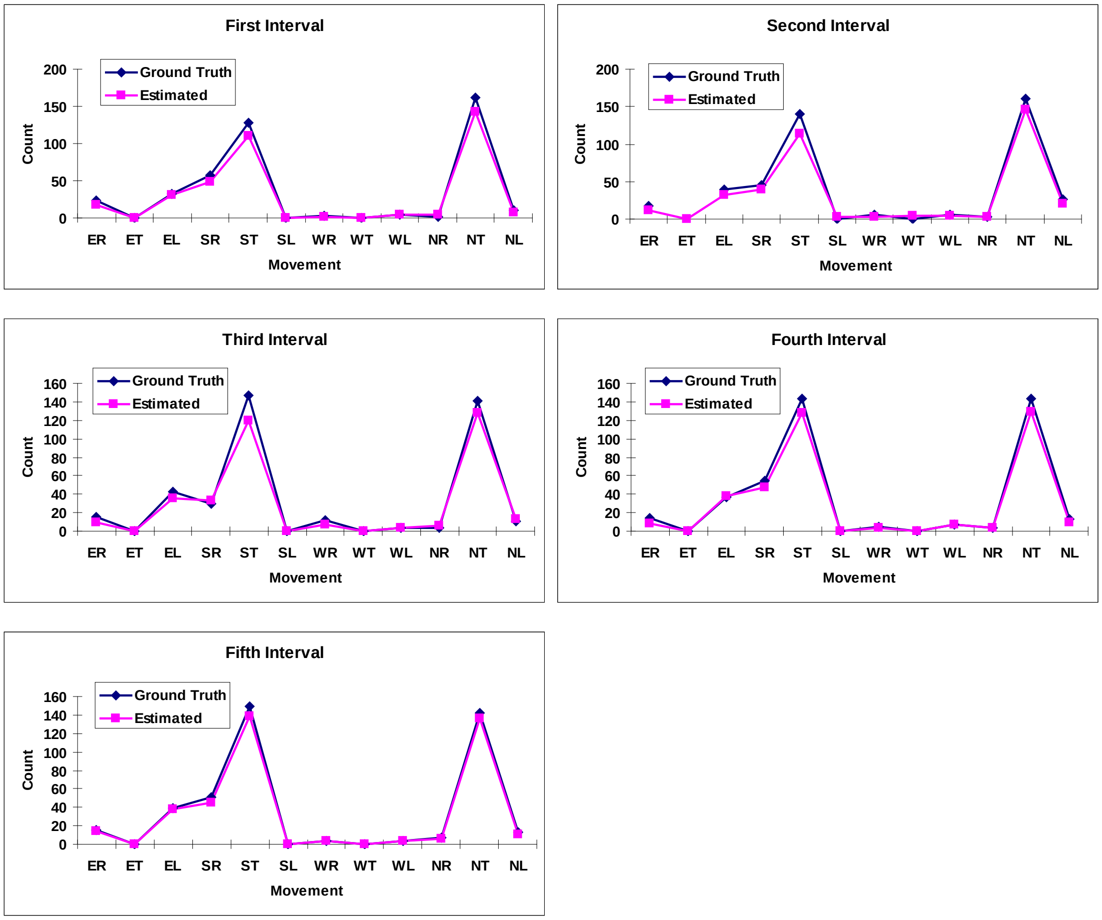


Figure 4.8 Laboratory Experiment Results on Wedgewood Avenue at Canton Road

From the above figures, we can find the estimated vehicle turning movements from ATMIS matches with the ground truth very well. The volume and the estimation error of each intersection are listed in Table 4.1. From this table, the overall error percentage is around 10% while the regular intersections perform better than irregular intersection. The difference between the error percentage of two regular intersections is very small (4.94% vs. 5.30%) which indicate ATMIS works well independent of the shared-lane condition. The error percentage of irregular intersection is around 13% which still can be accepted by most applications. The possible reason for worse performance of ATMIS on irregular intersection may be the longer and more complicated vehicle movement inside the intersection. Another noticeable point is that the detection error percentage is around 20% to 30% among all the experiments which indicates ATMIS has good error correction ability.

Table 4.1 Volume and Error Percentage of Laboratory Experiments

Time Interval	**Fifth & Arlington**		**Wilbeth & Arlington**		**Wedgewood & Canton**	
	Volume	**Error %**	**Volume**	**Error %**	**Volume**	**Error %**
1	461	6.49%	764	3.14%	422	14.22%
2	496	5.44%	811	6.66%	443	17.16%
3	505	4.75%	804	5.97%	407	16.46%
4	518	3.28%			421	12.11%
5					423	6.38%
Average	495	4.94%	793	5.30%	423.2	13.28%

4.2 Field Test

Even though the results of laboratory experiments are very encouraging, ATMIS still needs field test to verify its capability under real operation environment. During the field test, the first priority is not disturbing the normal traffic. The design of the system architecture for ATMIS in the field test is shown in Figure 4.9. The analog video signals from cameras are split into two outputs. One will go to the video detection unit in the cabinet to keep the detection for normal signal operation; and the other output will feed an extra video detection unit to collect the detection for vehicle turning movement identification. A SDLC data sniffer is used to capture the detections and signal status transferred on the SDLC bus in NEMA standard system. Under this architecture, everything in the cabinet remains the same and ATMIS is invisible to the system in the cabinet.

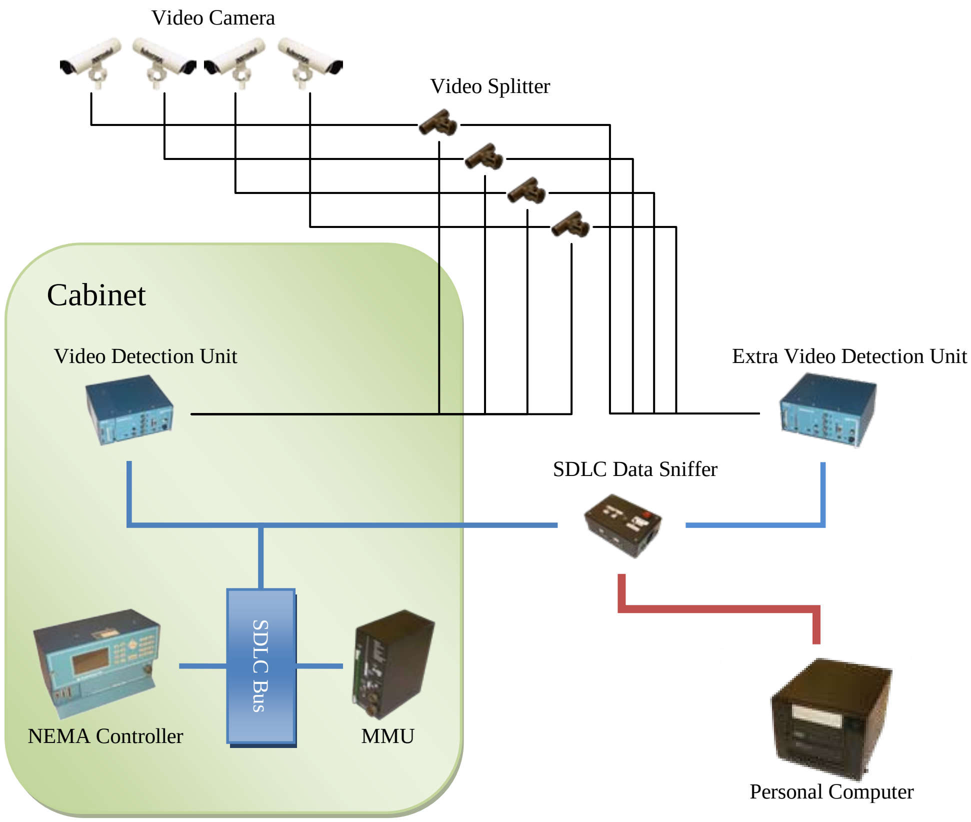


Figure 4.9 ATMIS System Architecture for Field Test

A field test was performed from 11:30 AM to 12:10 PM at the intersection of Fifth Avenue at South Arlington Road in March 17th 2008. The test result is shown in Figure 4.10 and the average error percentage is 7.89%. From the figure we can see that the estimated turning movements matched well with ground truth and the feasibility of ATMIS to be applied in field has been approved. The possible reason that field test result is not as good as the one in the laboratory is because of the lacking of detector calibration. In the laboratory experiments, we have plenty of time to adjust the position of the detectors and calibrate them while in the field test the calibration time is much shorter. Even though the result in field is not as good as the one in laboratory experiments, it still can fulfill the requirements of most applications.

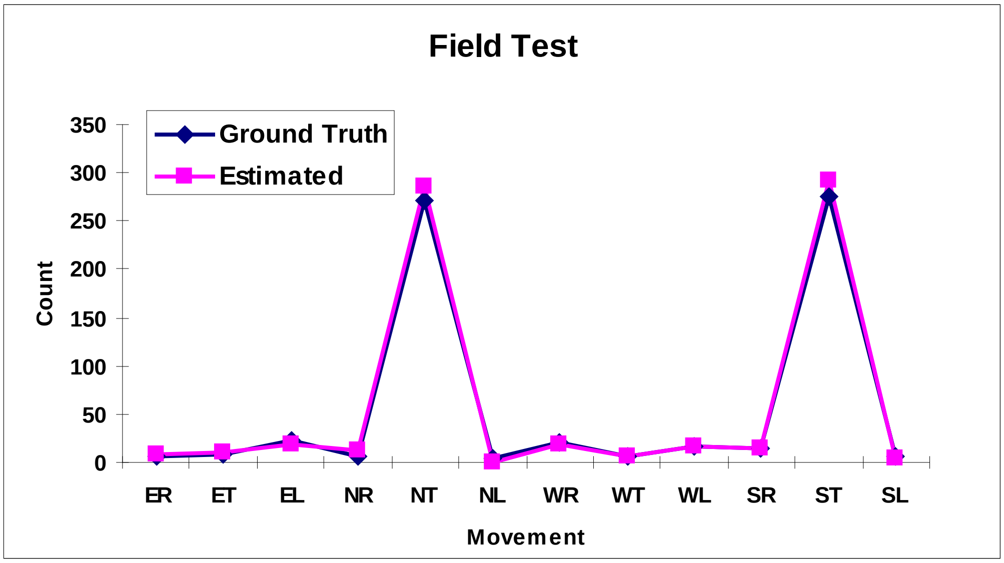


Figure 4.10 Field Test Result on Fifth Avenue and South Arlington Street

4.3 Detection Error

The errors of turning movements estimated in ATMIS are mainly caused by the detection error. The analyzing of detection errors will be helpful to calibrate the system to yield better estimation result and can be a good guide for later system application. Since all our experiments are based on visual detection system, the following discussion will only be applicable for visual detections.

4.3.1 Missing Count

Missing count means there is a vehicle passing the detector but the detection system failed to report it. In our tests, missing count could be caused by poor video quality, pavement-like vehicle color (Figure 4.11), obstructed following vehicle and the scope of the camera. To avoid missing count, we can improve the quality of the video to increase its sensitivity to the passing vehicles. Meanwhile, the height and angle of the camera are also very important to reduce the missing count caused by the scope of the camera.

Figure 4.11 Missing Counts

4.3.2 Double Count

Double count means there is no vehicle passing the detector but the detection system reports one. In our experiments, double count could be caused by non-vehicular object or vehicular object. Non-vehicular objects includes pedestrian, bicycles and sometimes even birds. This kind of double counts will be difficult to avoid in current visual detection system. Another kind of double counts caused by vehicular object could be a large size vehicle such as a truck (Figure 4.12), or a vehicle driving in the middle of two lanes, or even the different color of one vehicle, such as the color of windshield and its body. Adjustment of the height and angle of the camera could solve part of the double counts problem, but further improvement needs the advancement in visual detections system.

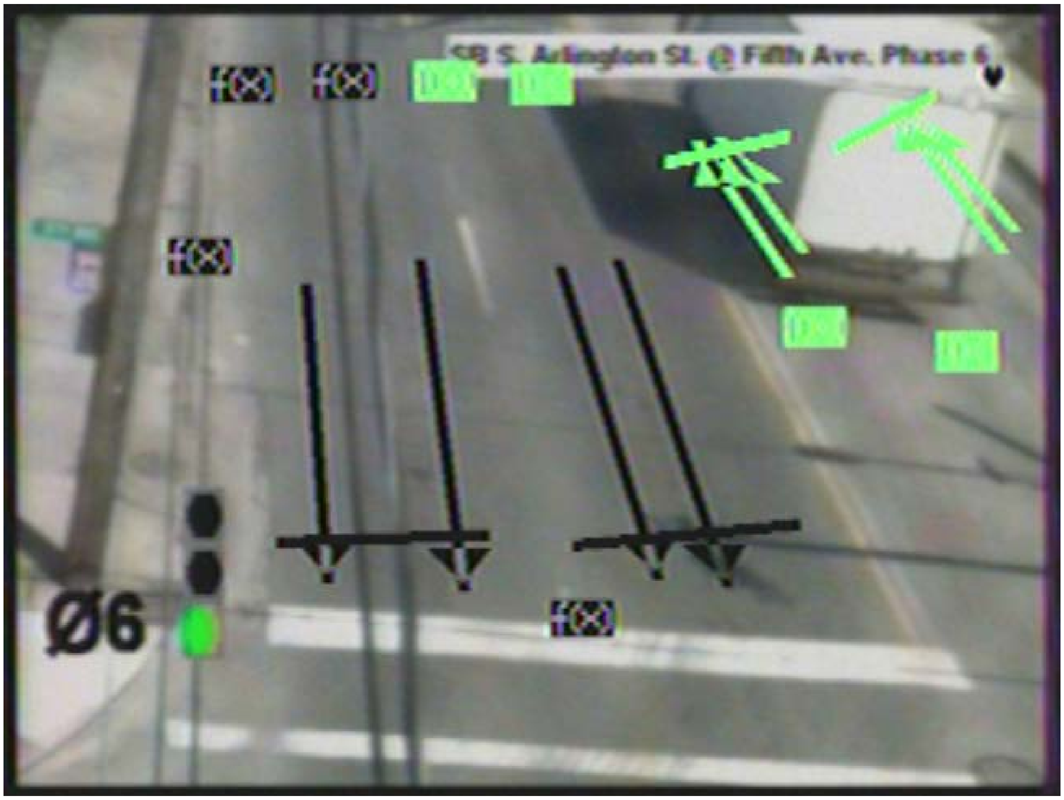


Figure 4.12 Double Counts

Since more detailed analysis of detection error is beyond the scope of this research, no more detection error analysis will be present in this thesis.

CHAPTER V

INTERSECTION DELAY MEASUREMENT

5.1 Introduction

ATMIS can be used in many applications including intersection delay measurement. According to the previous discussion, an automatic delay measurement method is necessary for intersection performance evaluation. One of the most direct MOE is vehicle control delay, which can be calculated by approach delay plus intersection delay. For approach delay, Teply suggested a good method to measure it while the intersection delay and delay for different turning movements are not addressed. Driven by the need of measuring intersection delay for different turning movements, a method based on the result of ATMIS is introduced and discussed in this thesis. The following section will discuss the methodology and the experiments of it.

5.2 Methodology

The purpose of the proposed methodology is to acquire the intersection delay from vehicles across the intersection. Same detector configuration from ATMIS is used in this study as shown in Figure 5.1. The gray detectors which are monitoring leaving vehicles are placed further downstream to allow the vehicles accelerating. With the assumption that vehicle returns to its free-flow speed when passing the leaving detectors, we can estimate the intersection delay by the following steps.

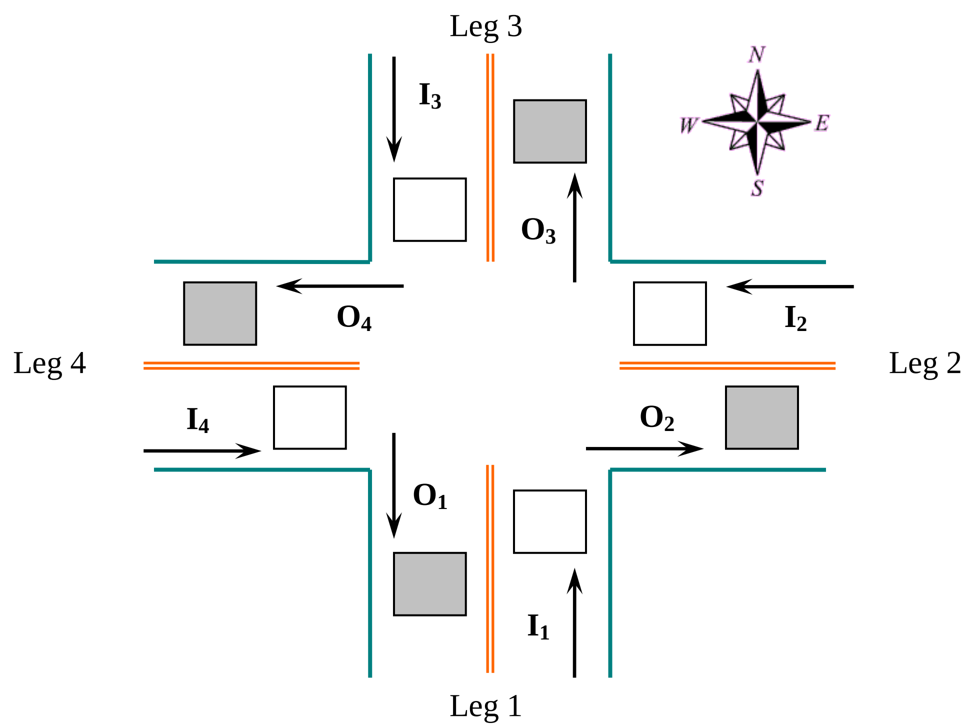


Figure 5.1 Detector Layout for Vehicle Intersection Delay Measurement

First, the timestamp of each vehicle turning movement, the arrival time I_m and leaving time O_n will be used to calculate the travel time with the following equation:

$$\sum TT_{O_n I_m} = a\left(\sum TS_{o_n} - \sum TS_{I_m}\right) \qquad 5.1$$

where,

a Video playing adjust factor

$TT_{o_n I_m}$ Estimated travel time for turning movement from I_m to O_n

TS_{O_n} Leaving timestamp for turning movement from I_m to O_n

TS_{I_m} Arrival timestamp for turning movement from I_m to O_n

The video playing adjust factor, ∂, is used to compensate faster or lower video playing speed. Thus, the average intersection delay can be measured by

$$Delay_{O_n I_m} = \frac{\sum TT_{O_n I_m}}{N_{o_n I_m}} - \min\left(TT_{o_n I_m}\right) \quad 5.2$$

$$\min(TT_{o_n I_m}) = \min\left(\frac{L_{O_n I_m}}{U_{o_n I_m}}, TT_{O_n I_m}\right) \quad 5.3$$

$\min\left(TT_{o_n I_m}\right)$ Free flow travel time or minimal travel time

$N_{o_n I_m}$ Number of vehicles turned from I_m to O_n

$L_{O_n I_m}$ Travel distance for turning movement from I_m to O_n

$U_{o_n I_m}$ Free flow speed for turning movement from I_m to O_n

The free flow travel time is set to either the minimal travel time or the calculated travel time, which one is smaller. The average vehicle delay for each approach then can be determined.

However the travel time estimated is not exactly the same as the ground truth because the ATMIS is unable to provide the precise data or the travel time results derived from the system. Therefore, further data filter is necessary to remove outlier. In statistics, an outlier is an observation that is numerically distant from the rest of the data. In practice, Grubbs' test is commonly used to detect outliers in a univariate data set. This test is based on the assumption of normality, that is, one should first verify that the data can be reasonably approximated by a normal distribution before applying the Grubbs' test (17, 18).

Grubbs' test detects one outlier at a time. This outlier is expunged from the dataset and the test is iterated until no outliers are detected. However, multiple iterations change the probabilities of detection, and the test should not be used for sample sizes of six or less since it frequently tags most of the points as outliers.

Grubbs' test is defined for the hypothesis:

H_0: There are no outliers in the data set

H_α: There is at least one outlier in the data set

The Grubbs' test statistic is defined as:

$$G = \frac{\max\limits_{i=1,2,3,\ldots.N} \left| Y_i - \overline{Y} \right|}{\varepsilon} \qquad 5.4$$

where,

$\overline{Y}$ Sample mean

ε Standard deviation

The hypothesis of no outliers is rejected at significance level of α if

$G > \frac{N-1}{\sqrt{N}} \sqrt{\frac{t^2_{(\alpha/(2N),N-2)}}{N-2+t^2_{(\alpha/(2N),N-2)}}}$ with $t_{(\alpha/(2N),N-2)}$ denoting the critical value of the t-distribution with (N-2) degrees of freedom and a significance level of α/(2N).

While travel time is estimated, no further conclusion can be promoted and stated until the estimated value and ground truth are compared through certain statistic methods. There are several widely applied statistics methods: for paired samples, two kinds T Tests are most commonly applied, which is any statistical hypothesis test in which the test statistic has a Student's t distribution if the null hypothesis is true and is applied when the population is assumed to be normally distributed but the sample sizes are small enough that the statistic on which inference is based is not normally distributed because it relies on an uncertain estimate of standard deviation rather than on a precisely known value:

Independent-Samples T Test: compare whether two samples are independent or not. And Independent samples mean that whether two samples are related or how they are related through accepting same measurement (19).

Paired-Samples T Test: compare the difference between two samples through mean one to one, which means the order of data can’t be switched (20).

However, referred to travel time, in this project, the data fail to satisfy normal distribution and homogeneity of variance. Therefore, non-parametric statistical tests, which do not rely on assumptions that the data are drawn from a given probability distribution, are alternative. Similarly for two samples test to T-test, two kinds nonparametric tests are most appreciated:

1. Two-Independent samples Test

Whether two independent samples are from same population distribution through the method to measure mean, median, scatter and skewness, such as Mann-Whitney U, Moses Test and Two-Samples Kolmogorov-Simirnov Test in SPSS (21):

Mann-Whitney U Test (also called the Mann-Whitney-Wilcoxon (MWW)): using the ranks of data to test the hypothesis that two samples of sizes m and n might come from the same population. (22)

Moses Test: In statistics, a distribution-free non-parametric test of the difference between two independent groups in the extremity of scores (in both directions) that the groups contain. Scores from both groups are pooled and converted to ranks, and the test statistic is the span of scores (the range plus 1) in one of the groups chosen arbitrarily. An exact probability is computed for the span and then recomputed after dropping a specified number of extreme scores from each end of its range.(Named after the US statistician Lincoln Ellsworth Moses (born 1921) who introduced it in 1952)(23).

Two-Samples Kolmogorov-Simirnov Test: The two-sample KS test is one of the most useful and general nonparametric methods for comparing two samples, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples (24, 25, 26).

2. 2-Related Samples Test

This nonparametric test is the extension of paired t-test, which tests whether two related rather than independent targeted samples follow same distribution or not. There are two methods recommended in SPSS:

Wilcoxon Sign Ranked Test: a test used in statistics to compare paired data, which has the advantage of incorporating the size of the difference between the two sets of data in comparison.

Sign Test: a test can be used to test the hypothesis that there is “no difference between the continuous distributions of two random variables X and Y.

5.3 Method Evaluation

In this section, it will be including data collection method, site selection criteria and statistical method to modify data.

5.3.1 Data collection

The following data or configuration is to collect:

a) Intersection Geometry

b) Signal Timing

c) Ground truth Intersection Travel Time

Autoscope system was applied to process all the detection information, Ground truth ITT was collected by four graduate students: one standing at stop bar recording the time the rear of vehicles leaving the stop bar, other three standing at other three possible departure bars recording the time of front of vehicle arriving departure bars. And intersection turning movements (TM) parameter is recorded by the three students as well. ATMIS presented is used to get the estimated turning movements information and estimated travel time.

5.3.2 Site selection

The proposed method is based on the ATMIS, therefore, S. Arlington and Fifth Ave was the best location to test our method, for its high TMI ratio (96.72%) and complete detection data recorded. The geometry and current signal timing plan is present in (Figure 4.5 (a)). And its 100 minutes traffic counts, estimated counts and TMI ratio are present at (Table 5.1)

Table 5.1 TMI Table

Start Day	3/10/2008					
Time	10:00-11:40					
Location	S. Arlington Rd @Fifth Ave					
TM	GT	E	AE	EP	VW	VWE
SR	47	53	6	12.77%	2.37%	0.30%
ST	761	754	7	0.92%	38.43%	0.35%
SL	24	21	3	12.50%	1.21%	0.15%
WR	70	75	5	7.14%	3.54%	0.25%
WT	48	32	16	33.33%	2.42%	0.81%
WL	48	52	4	8.33%	2.42%	0.20%
NR	35	42	7	20.00%	1.77%	0.35%
NT	829	835	6	0.72%	41.87%	0.30%
NL	18	16	2	11.11%	0.91%	0.10%
ER	20	25	5	25.00%	1.01%	0.25%
ET	21	21	0	0.00%	1.06%	0.00%
EL	59	63	4	6.78%	2.98%	0.20%
Overall	1980	1989	65	3.28%	100.00%	3.28%

5.3.3 Data Analysis

First, Grubbs' test will be used at each group data to identify outliers sequentially, because of the interior difference between the intersection geometries, driver behaviors, vehicles class, experiment time and so on in each groups, the outliers are different at each clip, generally the ITT should be small than 8 seconds for the vehicles across this intersection for South/Northbound through traffic (Table 5.2). And for south/northbound left turn, eastbound and westbound traffic, because of the volume of each turning movements is lower than 6 each clip and hence, no outlier identification method can be applied and hence only the average travel time between estimated value and ground truth will be described and compared.

Table 5.2 Outlier Range

Turning Movements	Outlier
NBT1	7
NBT2	7
NBT3	8
NBT4	9
SBT1	6
SBT2	6
SBT3	6
SBT4	6
NBR	8
SBR	11

Through Grubb's test, the outliers for each group are identified and removed. Further statistics test will be applied to test whether difference between the ground truth travel time and estimated travel time without outlier is significant or not, before the test, the distribution of two groups' data have to be identified above all. Because Paired Sample T-test requires the available data following Normal distribution and homogeneity of variance. And hence it is necessary to test the normality above further statistic analysis. Minitab is applied to test whether they follow normal distribution, which is used statistic software in general. From (Figure 5.2) it can be found that all the Normality Test is failed for the estimated value at each TM, the P-value <0.05, and hence paired-sample T-test is not available, therefore it is necessary to have another test: Non-parametric Test- Two Independent samples tests. And the selected data distribution and comparison displayed in (Figure 5.3, Figure 5.4, Figure 5.5).

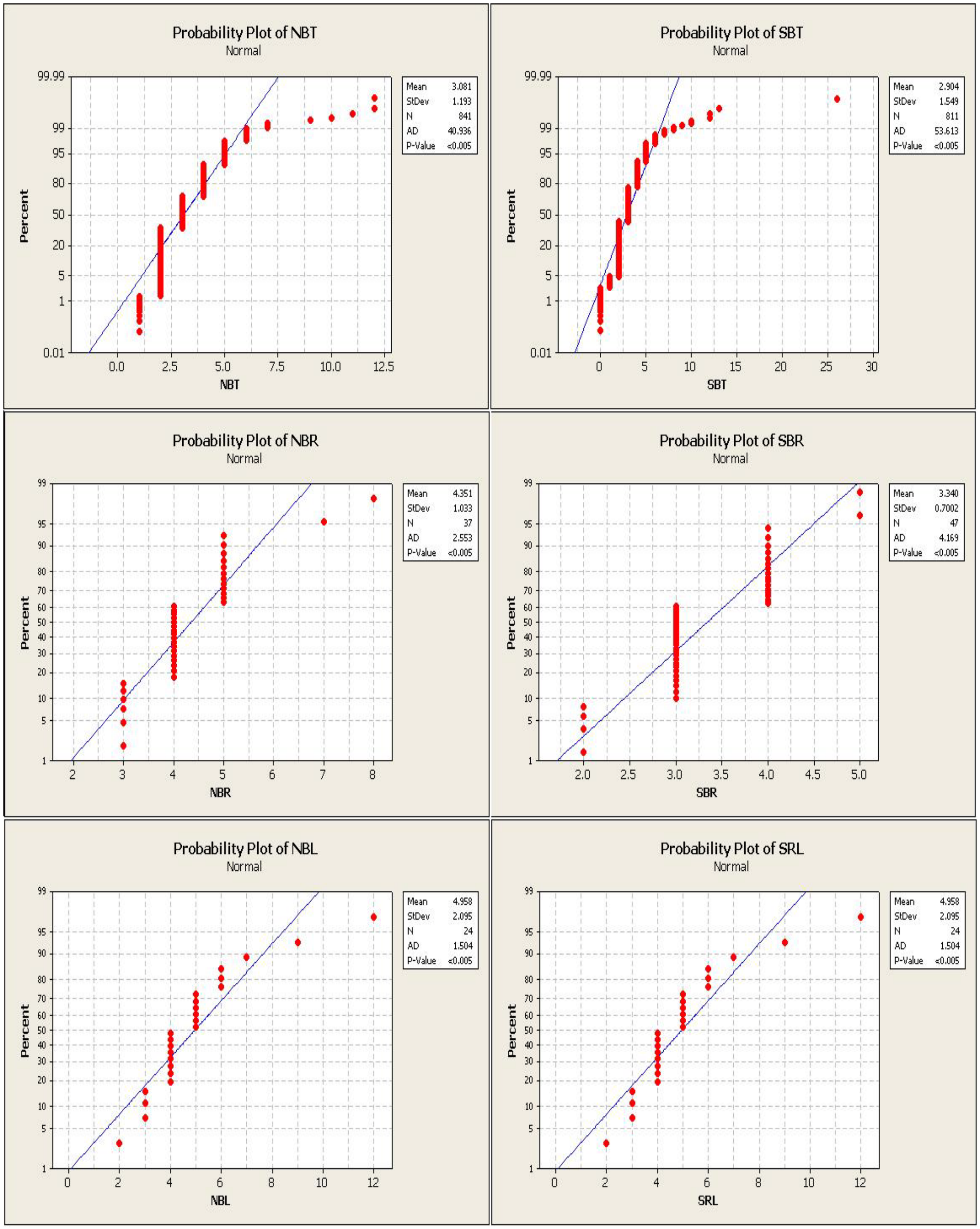


Figure 5.2 Normality Test

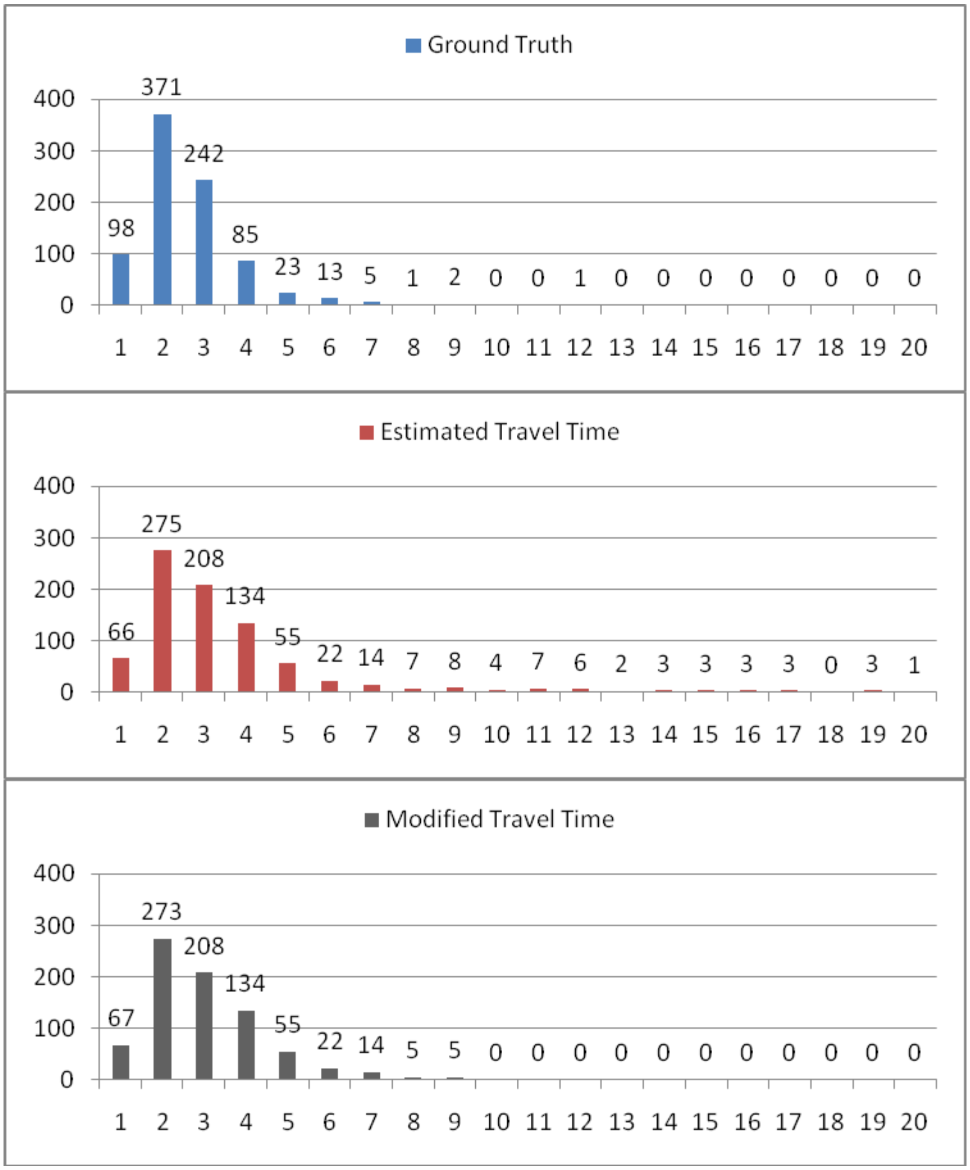


Figure 5.3 Northbound ITT Through Distribution

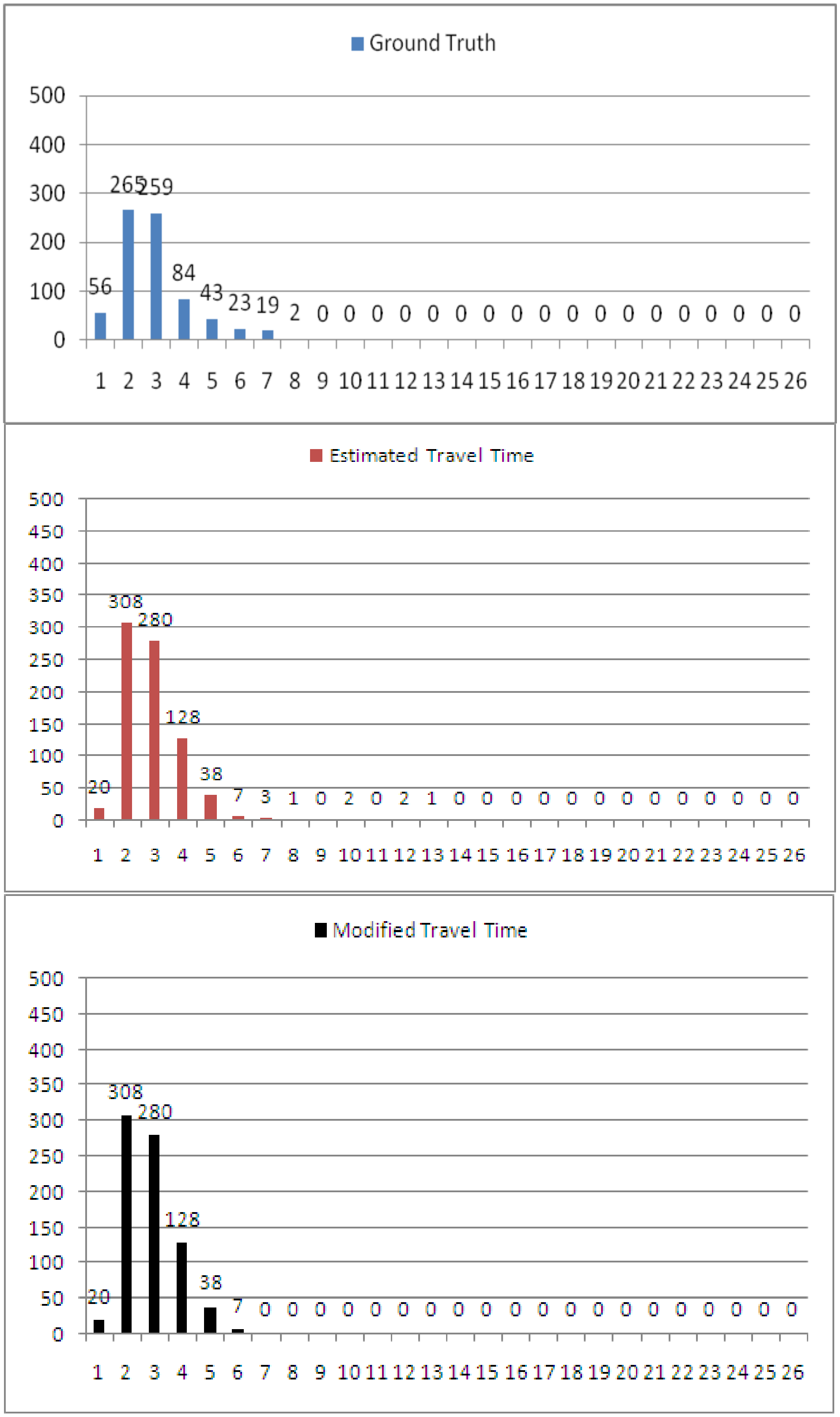


Figure 5.4 Southbound Through ITT Distribution

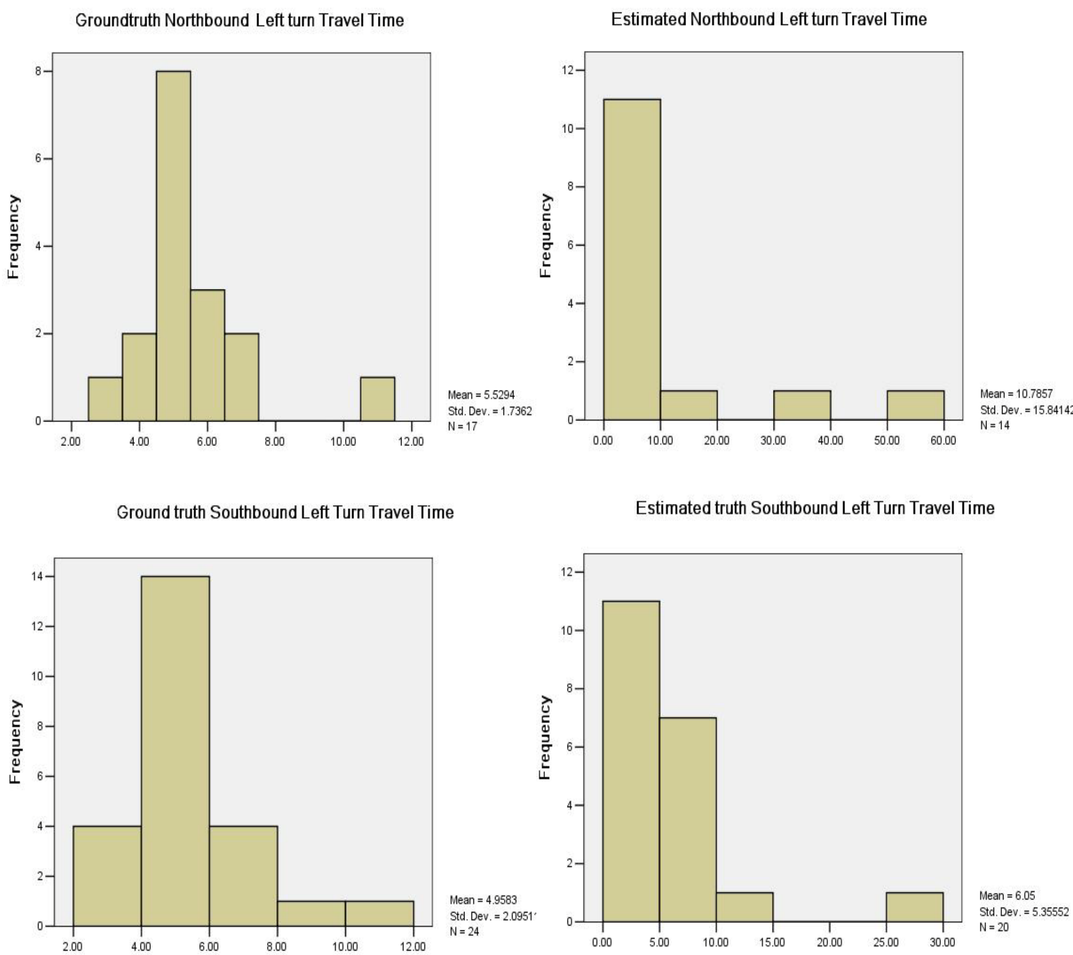


Figure 5.5 SB/NB Left Turn ITT Distribution

Based on the concept of Non-parametric test and due to the data based on three different measurements, ground truth by manually, estimated value by ATMIS and modified value by filtering estimated value, so the sequence of data are unmatched, and hence the three sample groups can be regarded as independent. Mann-Whitney U (MWU) Test is applied in each direction ITT to test whether the difference of corresponding groups is significant or not, and due to the low volume of NB/SBL and EB/WB ITT, Moose and Kolmogorov-Smirnov Z Test is not available. In SPSS, generally, there are each two tables in every group statements in WMU Test: In the first table the, first column states the targeted samples, the second column presents the total number of samples, the third column describes mean rank of each sample, and the last column shows the sum of ranks; in the second table, each line gives the parametric value of Mann-Whitney Test and Wilcoxon W and Z- Value, later based on Z-value, the result of two-tailed level of significance test can be found. From Figure 5.6, except the difference of the distribution of northbound through ITT between Ground truth an modified value is significant referred to WMU test, there is no significant difference of distribution between other modified ITT value with correspondent ground truth.

Ranks

	SBTgroup	N	Mean Rank	Sum of Ranks
SBT	GT	811	778.67	631504.00
	ET	779	813.02	633341.00
	Total	1590		

Test Statistics[a]

	GT vs ET
Mann-Whitney U	302238.0
Wilcoxon W	631504.0
Z	-1.562
Asymp. Sig. (2-tailed)	.118

a. Grouping Variable: SBTgroup

(a) SBT (GT vs. ET)

Ranks

	SBTgroup	N	Mean Rank	Sum of Ranks
SBT	GT	811	778.60	631442.00
	MT	751	784.64	589261.00
	Total	1562		

Figure 5.6 The Mann-Whitney Test of ITT

Test Statistics[a]

	GT vs MT
Mann-Whitney U	302176.0
Wilcoxon W	631442.0
Z	-.278
Asymp. Sig. (2-tailed)	.781

a. Grouping Variable: SBTgroup

(b) SBT (GT vs ET)

Ranks

	SBRgroup	N	Mean Rank	Sum of Ranks
SBR	1.00	47	45.03	2116.50
	2.00	52	54.49	2833.50
	Total	99		

Test Statistics[a]

	SBR
Mann-Whitney U	988.500
Wilcoxon W	2116.500
Z	-1.753
Asymp. Sig. (2-tailed)	.080

a. Grouping Variable: SBRgroup

(c) SBR (ET vs MT)

Ranks

	SBRgroup	N	Mean Rank	Sum of Ranks
SBR	1.00	47	45.03	2116.50
	3.00	46	49.01	2254.50
	Total	93		

Test Statistics[a]

	SBR
Mann-Whitney U	988.500
Wilcoxon W	2116.500
Z	-.773
Asymp. Sig. (2-tailed)	.439

a. Grouping Variable: SBRgroup

(d)SBR (GT vs ET)

Figure 5.6 The Mann-Whitney Test of ITT (continued)

Ranks

	SBLgroup	N	Mean Rank	Sum of Ranks
SBL	GT	24	22.44	538.50
	ET	20	22.58	451.50
	Total	44		

Test Statistics[a]

	GT vs ET
Mann-Whitney U	238.500
Wilcoxon W	538.500
Z	-.036
Asymp. Sig. (2-tailed)	.971

a. Grouping Variable: SBLgroup

(e) SBL (GT vs ET)

Ranks

	NBTgroup	N	Mean Rank	Sum of Ranks
NBT	GT	841	840.73	707052.50
	ET	843	844.27	711717.50
	Total	1684		

Test Statistics[a]

	GT vs ET
Mann-Whitney U	352991.5
Wilcoxon W	707052.5
Z	-.155
Asymp. Sig. (2-tailed)	.877

a. Grouping Variable: NBTgroup

(f) NBT (GT vs ET)

Ranks

	NBTgroup	N	Mean Rank	Sum of Ranks
NBT	GT	841	839.02	705616.50
	MT	783	784.01	613883.50
	Total	1624		

Figure 5.6 The Mann-Whitney Test of ITT (continued)

Test Statistics[a]

	GT vs MT
Mann-Whitney U	306947.5
Wilcoxon W	613883.5
Z	-2.458
Asymp. Sig. (2-tailed)	.014

a. Grouping Variable: NBTgroup

(g) NBT (GT vs MT)

Ranks

	NBRgroup	N	Mean Rank	Sum of Ranks
NBR	GT	35	33.14	1160.00
	ET	35	37.86	1325.00
	Total	70		

Test Statistics[a]

	GT vs ET
Mann-Whitney U	530.000
Wilcoxon W	1160.000
Z	-1.013
Asymp. Sig. (2-tailed)	.311

a. Grouping Variable: NBRgroup

(h) NBR (GT vs ET)

Ranks

	NBRgroup	N	Mean Rank	Sum of Ranks
NBR	GT	35	33.14	1160.00
	MT	29	31.72	920.00
	Total	64		

Test Statistics[a]

	GT vs MT
Mann-Whitney U	485.000
Wilcoxon W	920.000
Z	-.322
Asymp. Sig. (2-tailed)	.748

a. Grouping Variable: NBRgroup

(i) NBR (GT vs MT)

Figure 5.6 The Mann-Whitney Test of ITT (continued)

Ranks

	NBLgroup	N	Mean Rank	Sum of Ranks
NBL	GT	17	17.00	289.00
	ET	14	14.79	207.00
	Total	31		

Test Statistics[b]

	GT vs ET
Mann-Whitney U	102.000
Wilcoxon W	207.000
Z	-.692
Asymp. Sig. (2-tailed)	.489
Exact Sig. [2*(1-tailed Sig.)]	.518[a]

a. Not corrected for ties.

b. Grouping Variable: NBLgroup

(j) NBL (GT vs ET)

Figure 5.6 The Mann-Whitney Test of ITT (continued)

Non-parametric test only suggests whether the targeted samples follow same distribution by the means, median, scatter tendency and measurement of skewness, however, it does not provide any suggestion on the quality of measurements, mean, though Kruskal-Wallis H Test, a method of K-Independent samples Test regarded as One-way ANOVA of non-parametric test, does not concern Post Hoc Test, which compares the quality of each measurements. So, further statistic analysis, Repeated Measures Analysis of Variance, will be applied to compare the measurements. Repeated Measures Analysis of Variance is defined as:

When several measurements are taken on the same experimental unit (person, plant, machine, and so on), the measurements tend to be correlated with each other. When the measurements represent qualitatively different things, such as weight, length, and width, this correlation is best taken into account by use of multivariate methods, such as multivariate analysis of variance. When the measurements can be thought of as responses to levels of an experimental factor of interest, such as time, treatment, or dose, the correlation can be taken into account by performing a repeated measures analysis of variance (30).

In proposed data, three measurements (ground truth measured by hand, estimated value measured by ATMIS and Modified Value through ATMIS and Statistics process) are taken on the same experimental unit (ITT). And hence only North/Southbound Through and Right Turn 30-minute-average ITTs will be measured by Repeated Measures Analysis of Variance.

As ANOVA, it is necessary to verify the normality of data (Figure 5.7) and the Sphericity of variance (Figure 5.8), it can be found that N/SBT ITTs qualifies the criteria: normality and sphericity, and N/SBR ITTs failed at sphericity test, which there are 8 items listed in sphericity test, yet only the significance that we should concern: if the value of significance is larger than 0.05, it means that the variance of tested data are sphericit, and hence the test is only to process at the N/SBT ITTs. Through Repeated Measures ANOVA (Figure 5.9), the tests produced (Figure 5.10) are a type of post hoc test. As in the between-subjects case, the significant main effect only tells us that there is some significant difference between three conditions: it doesn't tell us the reason for this difference. SPSS does not perform Newman-Keuls for repeated measures designs. Instead, it tests the difference between successive levels of independent variable. And it can be found that estimated travel time is significantly different from Ground truth, but that Ground truth and Modified Value do not differ significantly both NB and SB through ITT. For Other direction ITT, no non-parametric methods are widely confirmed and appreciated until now. So, no further statistical analysis will process on other NB and SB ITT (31).

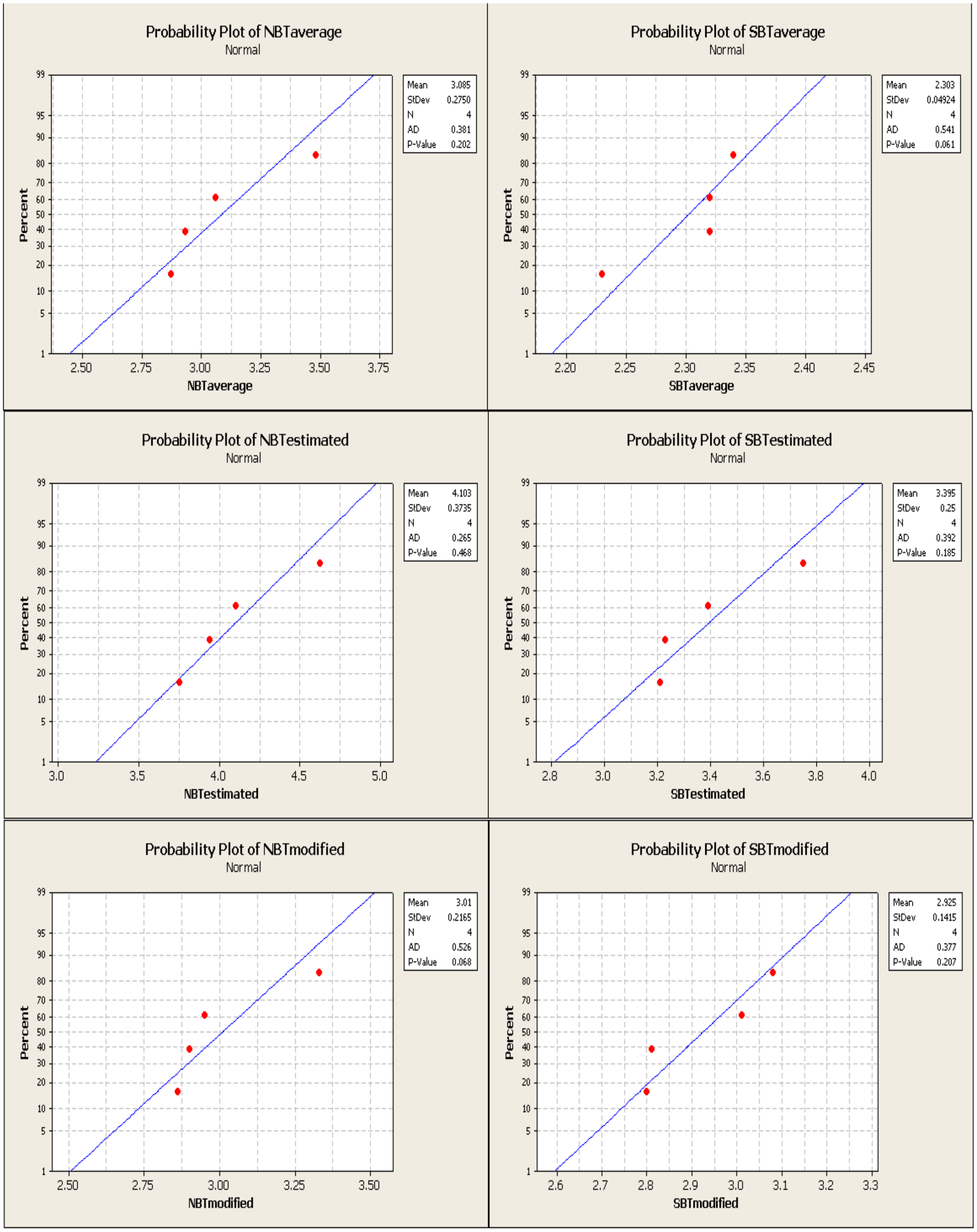


Figure 5.7 Normality Test of Average Travel Time

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
method	.081	5.038	2	.081	.521	.554	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b.
Design: Intercept
Within Subjects Design: method

(a) Shpericity Test of NBT through average ITT

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
method	.930	.145	2	.930	.935	1.000	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b.
Design: Intercept
Within Subjects Design: method

(b) Shpericity Test of SB through average ITT

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a] Greenhouse-Geisser	Huynh-Feldt	Lower-bound
method	1.000	.000	0	.	1.000	1.000	1.000

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b.
Design: Intercept
Within Subjects Design: method

(c) Shpericity Test of NB right turn average ITT

Figure 5.8 Shpericity Test

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
factor1	1.000	.000	0	.	1.000	1.000	1.000

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b.
Design: Intercept
Within Subjects Design: factor1

(d) Shpericity Test of SB right turn average ITT

Figure 5.8 Shpericity Test (continued)

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
method	Sphericity Assumed	2.976	2	1.488	26.195	.001
	Greenhouse-Geisser	2.976	1.042	2.856	26.195	.013
	Huynh-Feldt	2.976	1.107	2.688	26.195	.011
	Lower-bound	2.976	1.000	2.976	26.195	.014
Error(method)	Sphericity Assumed	.341	6	.057		
	Greenhouse-Geisser	.341	3.126	.109		
	Huynh-Feldt	.341	3.321	.103		
	Lower-bound	.341	3.000	.114		

(a) NB through Average ITT

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
method	Sphericity Assumed	.510	2	.255	9.515	.014
	Greenhouse-Geisser	.510	1.869	.273	9.515	.016
	Huynh-Feldt	.510	2.000	.255	9.515	.014
	Lower-bound	.510	1.000	.510	9.515	.054
Error(method)	Sphericity Assumed	.161	6	.027		
	Greenhouse-Geisser	.161	5.608	.029		
	Huynh-Feldt	.161	6.000	.027		
	Lower-bound	.161	3.000	.054		

(b) SB through Average ITT

Figure 5.9 Repeated Measures ANOVA Result

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	method	Type III Sum of Squares	df	Mean Square	F	Sig.
method	Level 1 vs. Level 2	4.139	1	4.139	24.463	.016
	Level 2 vs. Level 3	.022	1	.022	4.741	.118
Error(method)	Level 1 vs. Level 2	.508	3	.169		
	Level 2 vs. Level 3	.014	3	.005		

(a) NB through Average ITT Post hoc Test

Level 1: Estimated Travel Time

Level 2: Ground Truth

Level3: Modified Travel Time

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	method	Type III Sum of Squares	df	Mean Square	F	Sig.
method	Level 1 vs. Level 2	.608	1	.608	10.440	.048
	Level 2 vs. Level 3	.028	1	.028	.439	.555
Error(method)	Level 1 vs. Level 2	.175	3	.058		
	Level 2 vs. Level 3	.189	3	.063		

(b) NB through Average ITT Post hoc Test

Figure 5.10 Repeat Measures ANOVA Post hoc Test Result

5.4 Delay Measurement

Based on the modified estimated ITT and Equation 5.2, the delay for each turning movements can be estimated, each min travel time of estimated value or that measured according to HCM vehicle classifications will be regarded as free flow travel of turning movements. At proposed method, min travel time at each TM ITTs is regarded as free flow travel time, for few large size vehicles driving through this intersection (Table 5.3)

Table 5.3 Delay Estimation Table

ITT	Travel Time	Min Travel Time	Delay
NBT video1	2.90	1	1.90
NBT video2	2.95	1	1.95
NBT video3	2.86	1	1.86
NBT video4	3.33	1	2.33
SBT video1	3.01	1	2.01
SBT video2	3.08	1	2.08
SBT video3	2.80	1	1.80
SBT video4	2.81	1	1.81
NBR	4.28	2	2.28
SBR	3.48	2	1.48
NBL	10.79	1	9.79
SBL	6.05	2	4.05

Table 5.3 presents that through traffic cost less travel time than the left turn and right turn traffic at both average travel time and min travel time, mean, the average left turn travel time is similar to the average right turn travel time, however, the average travel time of left turn traffics is much higher than the average travel time of right turn traffics. Thus results obey the consensus.

In real-time, due to the different traffic time and traffic condition, the ITT and delay may be various at the same intersection. So, the process of data filter should be proceeding according to traffic demand in order not to filter certain plausible outliers, and free flow travel depends on the geometry of intersections.

CHAPTER VI

CONCLUSION AND FUTURE WORK

In this thesis, a cost-efficient method, Automatic Turning Movement Identification System, to get precise turning movement information, has been presented and discussed. Based on the above discussions, the result of ATMIS is quite encouraging and the average 5% error at regular intersections is competitive to other methods. Its reliable performance on handling shared-lane intersections has been demonstrated during the tests. For irregular intersection, ATMIS also yields an acceptable error (about 15%) for vehicle turning movements. In the future, more intersections are recommended to be involved in the experiments and more field tests are going to be conducted.

The application of ATMIS in intersection delay estimation is also introduced in this thesis. With further data filtering, vehicle turning movement information from ATMIS can be used to generate reliable intersection delay for different turning movements. Statistical analysis has shown that there is no significant difference between estimated vehicle delay and the ground truth. In the future, we can integrate this method with approach delay measurement to estimate vehicle delay precisely and automatically. The application of this method in traffic network can also be tested and applied.

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APPENDICES

APPENDIX A

REPEATED MEASURES ANOVA TEST FOR AVERAGE ITT

General Linear Model---Repeated Measures ANOVA (NBT Mean)

Within-Subjects Factors

Measure: MEASURE_1

method	Dependent Variable
1	Estimated NBmean
2	NBGTMean
3	Modified NBmean

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
method	Pillai's Trace	.915	10.777[a]	2.000	2.000	.085
	Wilks' Lambda	.085	10.777[a]	2.000	2.000	.085
	Hotelling's Trace	10.777	10.777[a]	2.000	2.000	.085
	Roy's Largest Root	10.777	10.777[a]	2.000	2.000	.085

a. Exact statistic

b.
Design: Intercept
Within Subjects Design: method

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
method	.081	5.038	2	.081	.521	.554	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b. Design: Intercept
Within Subjects Design: method

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
method	Sphericity Assumed	2.976	2	1.488	26.195	.001
	Greenhouse-Geisser	2.976	1.042	2.856	26.195	.013
	Huynh-Feldt	2.976	1.107	2.688	26.195	.011
	Lower-bound	2.976	1.000	2.976	26.195	.014
Error(method)	Sphericity Assumed	.341	6	.057		
	Greenhouse-Geisser	.341	3.126	.109		
	Huynh-Feldt	.341	3.321	.103		
	Lower-bound	.341	3.000	.114		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	method	Type III Sum of Squares	df	Mean Square	F	Sig.
method	Level 1 vs. Level 2	4.139	1	4.139	24.463	.016
	Level 2 vs. Level 3	.022	1	.022	4.741	.118
Error(method)	Level 1 vs. Level 2	.508	3	.169		
	Level 2 vs. Level 3	.014	3	.005		

Tests of Between-Subjects Effects

Measure: MEASURE_1
Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	46.201	1	46.201	919.884	.000
Error	.151	3	.050		

General Linear Model--- Repeated Measures ANOVA (SBT Mean)

Within-Subjects Factors

Measure: MEASURE_1

method	Dependent Variable
1	Estimated SBTmean
2	SBTGTmean
3	Modified SBTmean

Multivariate Tests[b]

Effect		Value	F	Hypothesis df	Error df	Sig.
method	Pillai's Trace	.893	8.380[a]	2.000	2.000	.107
	Wilks' Lambda	.107	8.380[a]	2.000	2.000	.107
	Hotelling's Trace	8.380	8.380[a]	2.000	2.000	.107
	Roy's Largest Root	8.380	8.380[a]	2.000	2.000	.107

a. Exact statistic

b.

Design: Intercept
Within Subjects Design: method

Mauchly's Test of Sphericity[b]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[a]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
method	.930	.145	2	.930	.935	1.000	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

b.

Design: Intercept
Within Subjects Design: method

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
method	Sphericity Assumed	.510	2	.255	9.515	.014
	Greenhouse-Geisser	.510	1.869	.273	9.515	.016
	Huynh-Feldt	.510	2.000	.255	9.515	.014
	Lower-bound	.510	1.000	.510	9.515	.054
Error(method)	Sphericity Assumed	.161	6	.027		
	Greenhouse-Geisser	.161	5.608	.029		
	Huynh-Feldt	.161	6.000	.027		
	Lower-bound	.161	3.000	.054		

Tests of Within-Subjects Contrasts

Measure: MEASURE_1

Source	method	Type III Sum of Squares	df	Mean Square	F	Sig.
method	Level 1 vs. Level 2	.608	1	.608	10.440	.048
	Level 2 vs. Level 3	.028	1	.028	.439	.555
Error(method)	Level 1 vs. Level 2	.175	3	.058		
	Level 2 vs. Level 3	.189	3	.063		

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	38.632	1	38.632	1833.219	.000
Error	.063	3	.021		

APPENDIX B

LIST OF ABBREVIATIONS

EB: Eastbound

ET: Estimated Travel Time

ITT: Intersection Travel Time

GT: Ground truth

MT: Modified Travel Time

SB: Southbound

SBR: Southbound Right Turn

SBL: Southbound Left Turn

SBT: Southbound Through

TM: Turing Movements

NB: Northbound

WB: Westbound

MOE: Measure of Effectiveness

OD: Original Destination

ATMIS: Automatic Turning Movements Identification System

TMI: Turning Movements Identification