Vehicle Reidentification with the Inductive Loop Signature Technology

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Abstract: This study proposed a real-time inductive loop signature based vehicle reidentification approach, RTREID-2M, which improved the previously developed RTREID-2 algorithm on two aspects: (1) Develop a cubic spline data imputation approach to replace the existing linear data imputation approach in order to improve the raw signature data quality; (2) Improve the time window setting for vehicles on High-Occupancy Vehicle (HOV) lanes so that vehicles on HOV lanes traveling with free flow speeds would be considered when generating candidate vehicle sets even during congestion time periods. In addition, a stratified-random sampling method was developed to effectively perform grouth-truthing task for evaluating the performance of the proposed RTREID-2M. The evaluation results showed desired performance for vehicle reidentification and travel time estimation under both free-flow and congested flow traffic conditions. The future research will focus on the potential applications and arterial vehicle reidentification utilizing the inductive loop signature technologies.

Keywords: Vehicle Tracking, Vehicle Reidentification, Vehicle Signature, Inductive Loop Signature, Inductive Loop Detectors, Travel Time

1. INTRODUCTION

Inductive Loop Detector (ILD) systems are currently the most invested technology for obtaining traffic data in the United States and are widely deployed on many major freeway networks. Inductive loop detectors are connected to traffic controllers via conventional bivalent ILD cards and they provide traffic agencies with accurate volume and occupancy information. When installed in a double loop speed trap configuration, they can also provide point speed and electronic vehicle length information. Otherwise, aggregate traffic speed information is usually estimated using other methods, which assume some representative static or dynamic electronic vehicle length value commonly known as the g-factor (Wang and Nihan, 2003). However, this speed information is a point-based measure. It does not capture traffic conditions between detector stations and hence may not accurately represent prevailing traffic conditions along a corridor. This is especially a concern during unstable traffic conditions when traffic flow exhibits the highest volatility and compressibility.

Although the data obtained from conventional ILD systems is not suitable for obtaining origin-destination information, conventional ILD systems are found to be used to generate various traffic performance measures. However, the measures they provide, such as volume, point speed estimates, and density estimates, are primitive, and assumptions and factor adjustments are required to yield sufficient insight and certainty of knowledge needed for making key decisions in traffic operations and management.

Unlike the conventional ILD systems that provide bivalent outputs to indicate vehicle presence, the inductive loop signature-based detector systems measure and output the inductance changes (referred as "Magnitude") in an inductive loop detector. This series of inductance changes caused by each traversing vehicle produce an analog waveform output and is referred to as the inductive vehicle signature. Inductive loop signature-based systems have shown the potential to address the needs of traffic management agencies and have the advantage of being directly compatible with existing traffic controllers and Traffic Management Center (TMC) operations.

The existing conventional ILD systems can be swapped directly with the inductive loop signature-based detector systems without suffering any loss in system functionality. Another advantage of inductive loop signature technology is its ability to harness the vast infrastructure of the currently installed base of inductive loop detectors. The loop signature technology has been further implemented in the real-world and its performance has been demonstrated through academic research (Jeng et al., 2010; Tok et al., 2008). Additionally, it has been demonstrated that the implementation of inductive loop signature equipment does not affect existing traffic operations and management systems. No pavement work, and thus no lane closure or traffic rerouting, is required to integrate an inductive loop signature-based system.

Therefore, a real-time inductive loop signature-based vehicle reidentification algorithm is proposed in this study. A vehicle tracking system between two locations using inductive loop signature technology is performed to demonstrate the capability and accuracy of the proposed methods. A ground-truthing system and evaluation procedure will be developed for system assessment and input into a rigorous statistical analysis comparing the tracked vehicles against the ground-truthed vehicles.

2. INDUCTIVE LOOP SIGNATURE TECHNOLOGY

2.1 Inductive Vehicle Signatures

As mentioned above, the inductive vehicle signature is an analog waveform output from the inductive loop signature-based detector systems. Samples of inductive vehicle signatures for various vehicle types are presented in Figure 1, which shows that there are clear distinctions observed in the signatures across different vehicle types.

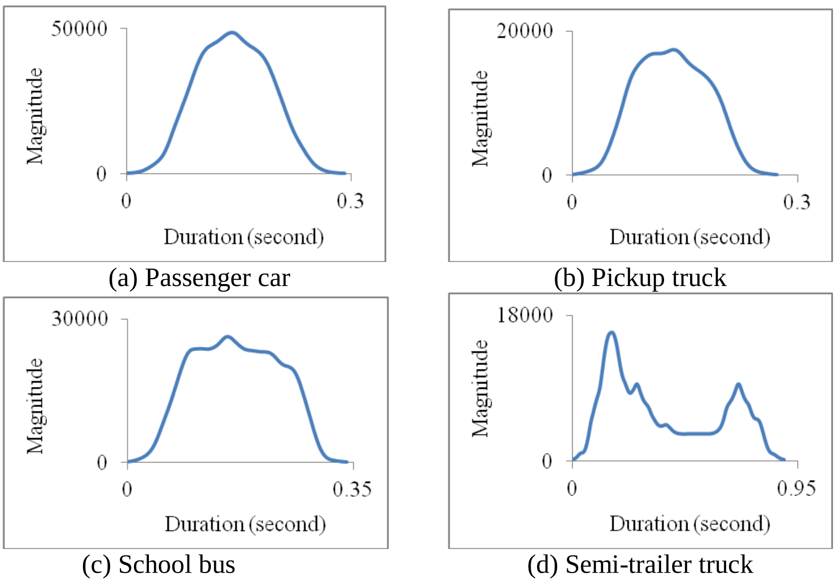
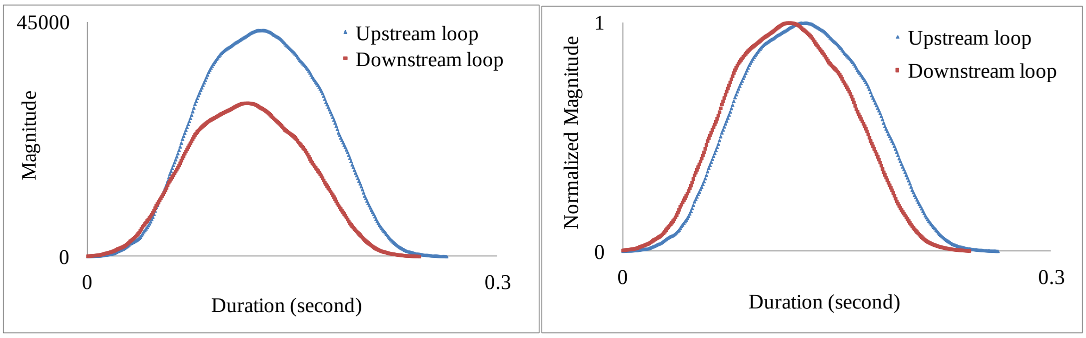
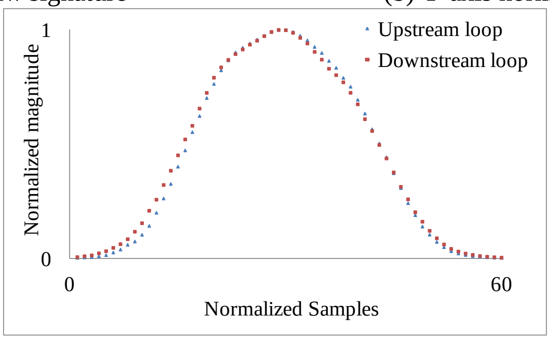


Figure 1. Inductive vehicle signatures obtained from a 6-ft square inductive loop detector

The reason for different vehicle types having different shapes of signatures are due to their different attributes, including size, mental mass, axles, distance between the metal surfaces on the under carriage of the vehicle and the road surface, etc. For vehicles of the same type, their signatures have many similarities due to the similar vehicle design. For the same vehicle, its signatures at different loop detector stations are identical in ideal conditions (Sun et al., 1999); however, they are usually very similar but not the same. This is because a loop detector station is composed of a few components, including the roadway geometry, physical inductive loop detector, lead-in cables, and detector circuitry. The signatures change with vehicle speed, vehicle offset (both horizontally and vertically), loop type, loop condition and detection sensitivity settings, etc. Figure 2(a) shows a vehicle's signatures at two adjacent loop detector stations. They look different vertically and horizontally. The vertical differences are due to the different detectors, vehicle offset, and external environmental factors. The horizontal differences are mainly caused by different traveling speeds.



(a) Raw signature (b) Y-axis normalized signature



(c) Processed signatures after X-axis and Y-axis normalization

Figure 2. Raw and normalized signatures for the same vehicle at different loop detector stations (Jeng et al., 2012)

Figure 2(b) and Figure 2(c) illustrates that the signatures from the same vehicle are very alike at different loop stations after performing x and y normalization. Figure 2(b) shows the processed signatures after y-axis normalization. Figure 2(c) shows the processed signatures after x-axis normalization, which only keeps 60 data points along the x-axis for both signatures.

The signatures' similarities for the same vehicle and among vehicles of the same type are the basis for vehicle tracking and classification using the inductive loop signature technology. Some existing research shows that when inductive vehicle signatures are matched across adjacent ILD stations, measures such as section-based speeds, travel times, and densities can be obtained (Oh et al., 2005; Jeng et al., 2010; Kwon and Parsekar, 2006; Oh and Ritchie, 2005). These measures can be further analyzed by vehicle type or by lane to yield even more detailed travel information if required. Researchers have also shown that inductive loop signature technology possesses the ability to distinguish between passenger and commercial vehicle classes in the FHWA (Federal Highway Administration) vehicle classification scheme (Sun et al., 2003; Jeng and Ritchie, 2008; Gajda et al., 2001; Ki and Dail, 2005). This addresses the limitations of axle-based classification systems, which have problems distinguishing between passenger vehicles and light duty trucks as well as between single unit trucks and buses (Wang and Nihan, 2003; Zhang et al., 2006; Coifman and Kim, 2009).

Considering the vast infrastructure of the currently installed inductive loop detectors, the inductive loop signature technology has the potential to make the existing traffic performance measurement system collect more useful and accurate data for traffic information and traffic control and management applications.

2.2 Inductive Loop Signature-based Vehicle Reidentification Algorithms

One of the major research efforts for the implementation of the inductive loop signature technology is the development of inductive signature based vehicle reidentification algorithms. These algorithms reidentify a vehicle at a downstream detection station by matching an inductive signature from an upstream detection station based on the assumption that a vehicle will possess essentially the same normalized inductive signature when passing different loop detection stations (Sun et al., 1999). Researchers have developed several vehicle reidentification algorithms, including Piecewise Slope Rate (PSR) matching (Jeng et al., 2010; Jeng and Ritchie, 2006), Lexicographic Optimization (Sun et al., 1999; Oh and Ritchie, 2002), decision trees (Tawfik et al., 2004; Abdulhai and Tabib; 2003), maximum a-priori classifier (Ndoye et al; 2008), and blind deconvolution (Kown and Parsekar, 2006). Each of the studies adopts various techniques for raw signature processing, signature feature extraction, and vehicle matching.

A PSR matching method, named RTREID-2 (Jeng and Ritchie, 2006) is adopted for further investigation in this study. The RTREID-2 reidentifies a vehicle at a downstream detection station by matching PSRs of inductive signatures from an upstream detection station. The PSR approach is employed to compress and transform the raw vehicle signatures first. Vehicle matches are then identified based on search methods applied to the averaged PSR differences within appropriate time windows. The advantage of RTREID-2 is its straightforward application to square or round inductive loop detectors in a single loop configuration. The results reported from the algorithm development have shown that with 30 PSR values extracted, the correct matching rate was 80.8% and the system reliability was 81.9% under light to moderate flow condition.

Another study by Jeng et al. (2012) reported the results of a 6.2-mile freeway corridor implementation of RTREID-2 to provide traffic performance measurements under congested morning peak-period conditions. The repeatability of RTREID-2 was first examined using square single loop data, and then the applicability of RTREID-2 was assessed using round single loop data. The transferability of RTREID-2 to a heterogeneous detection system, including one square single loop detection station and one round single loop detection station, was also investigated. The corridor travel time and speed analysis were conducted and compared with GPS measurements from probe vehicles. The correlation between GPS and RTREID-2 speeds was also examined, and strong positive association between GPS speeds and RTREID-2 speeds was observed. The results suggest that RTREID-2 has the potential to be implemented successfully in freeway corridors that experience frequent congestions. Moreover, the flexibility of utilizing either a single type or a combination of existing round and square inductive loop detector infrastructure has made RTREID-2 readily deployable to most inductive loop detector equipped corridors.

In this study, RTREID-2 is further improved to address noises observed in vehicle signatures and refine the time window setting for vehicles traveling on the High-Occupancy Vehicle (HOV) lanes. The detailed discussions on RTREID-2 and the proposed modification to RTREID-2, which is referred to as RTREID-2M, are described in the next section.

3. METHODOLOGY

3.1 Existing RTREID-2 Algorithm

RTREID-2 is the third generation of vehicle reidentification algorithm developed by the research team at University of California, Irvine (UCI). Unlike the first two generations of algorithms, REID-1 (Sun et al., 1999) and REID-2 (Jeng and Ritchie, 2005) that were designed for the off-line use, RTREID-2 was designed to reidentify vehicles in near real-time. RTREID-2 needs the field computers to extract the feature data, i.e., 30 PSR values, from the raw vehicle signatures, which typically consist of 200~1,800 data points. The PSRs are then sent to the center where vehicles are reidentified through matching PSRs. RTREID-2 provides a practical solution because of the use of less computational resources for signature data preprocessing and less communication bandwidth for data transmission.

The procedure of data preprocessing and vehicle reidentification procedure in RTREID-2 can be summarized in seven steps (further details can be found in Jeng and Ritchie, 2006; Jeng et al., 2010).

Step 1: Data Cleaning and Imputation. After getting raw signature data from loop signature detector card, the bad signature data are removed. The remaining signature data are analyzed and the missing data are imputed using a linear interpolation method.

Step 2: Normalization and Noise Elimination. The inductance value (i.e., magnitude) of each individual vehicle is normalized using its range so that the normalized magnitudes distribute from 0 to 1. The normalization process is applied to eliminate the vertical differences between signatures from the same vehicle at different detection stations.

Step 3: Noise Elimination. The signature data may be full of noises when the magnitude is low. As a result, the lowest 20% (which is a tunable parameter) of the magnitudes is considered as noises and is removed. Thus, only a subset of each vehicle signature that the normalized magnitudes from Step 2 are within the range from 0.2 to 1.0 is extracted in order to eliminate noise caused by the external environment factors.

Step 4: Interpolation. The signature data are stretched or shrunk to obtain an identical number of data points per vehicle signature using a cubic spline method (Figure 3(a)). The process is used to eliminate the horizontal differences between signatures since vehicles may be traveling with different speeds at different detection stations.

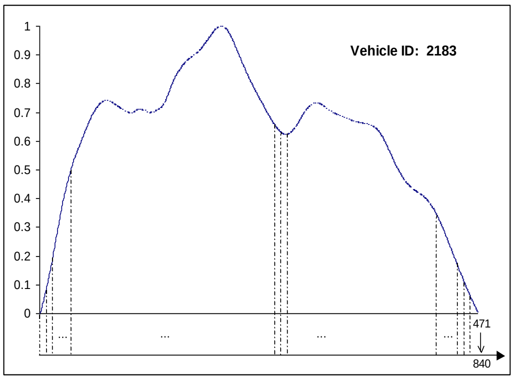
Step 5: Piecewise Slope Rate (PSR) Calculation. The slope rate is calculated at a fixed interval size. The interval size used in the current RTREID-2 is 2. Thus, a signature with 60 data points has 30 PSR values as shown in Figure 3(b) and Figure 3(c). For example, if assuming the data point located at $\left(x_1,\ y_1\right)=\left(2,\ 0.2236\right)$ and the next data point is located at $\left(x_2,\ y_2\right)=\left(4,\ 0.4747\right)$, then the slope rate is:

$$(y_2 - y_1)/(x_2 - x_1) = (0.4747 - 0.2236)/(4-2) = 0.12555.$$

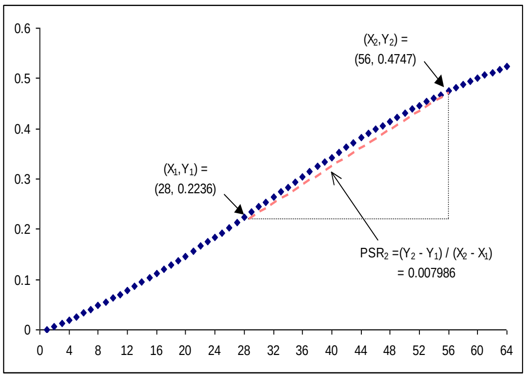
Step 6: Candidate Vehicle Set Formation. A candidate vehicle set is defined via temporal search space reduction for establishing a feasible time period to include possibly matched vehicles at upstream detection station. The time window is estimated based on real-time traffic condition and the time window of the last 30-second time interval.

Step 7: Vehicle Matching. Every 30 sec, a vehicle matching process is performed as shown in Figure 3(d). This process includes several sub-steps:

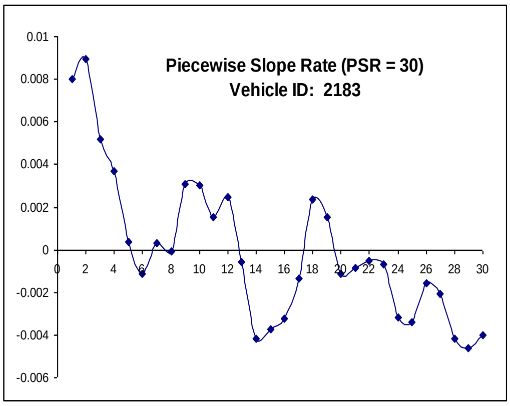
1) Compute and sum the differences between PSRs obtained from the downstream target vehicle and each upstream candidate vehicle;
2) Find the Average of the total PSRs Differences (AMD);
3) Perform a minimum AMD search to decide the best match.



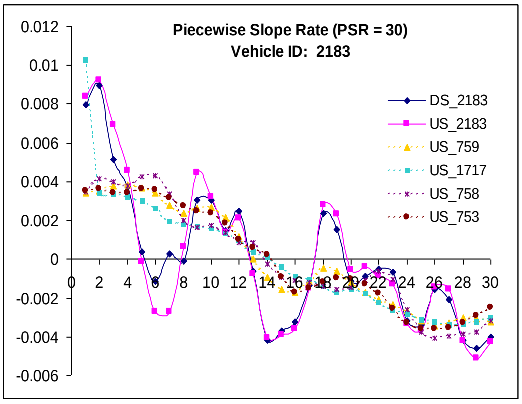
(a) Step 4: Data Interpolation (CASE_840)



(b) Step 5: PSR Calculation



(c) Step 5: PSR Plot



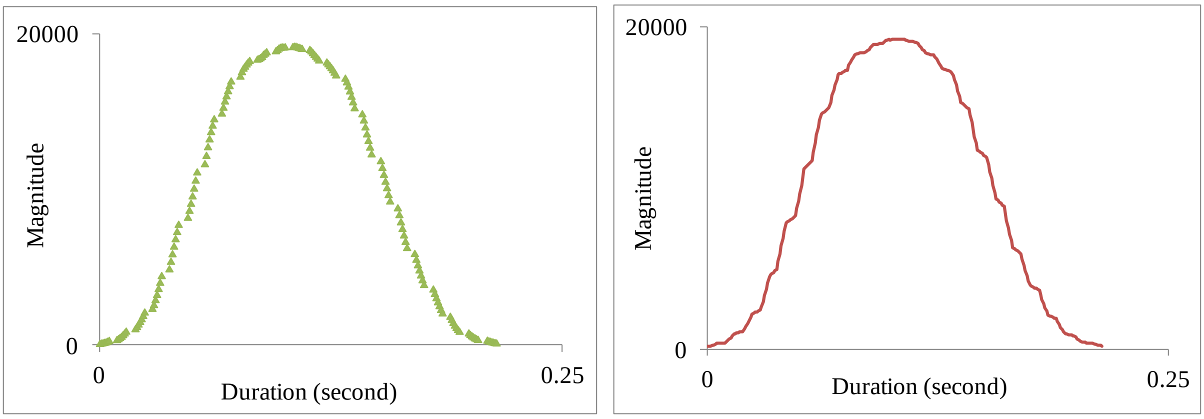
(d) Steps 7: Vehicle Matching

Figure 3. The procedure of RTREID-2 (Jeng and Ritchie, 2006)

3.2 Improvement of RTREID-2

3.2.1 Data Imputation Algorithms

Data missing is frequently observed when a vehicle travels with a higher speed (i.e., shorter duration on the loops) or when frequent interference from adjacent lanes is observed (e.g., under congestion condition). As explained in 3.1, a linear data imputation approach is adopted in RTREID-2 to fill in the missing data when signature data is collected from the detector card. The linear data imputation approach is effective when few signature data dropping is present. However, when many signature data are dropped, the approach is not suitable and the signature after imputation presents the zigzag patterns as shown in Figure 4. The dataset may become very noisy (e.g., the dataset used in this study) and the original RTREID-2 will not perform sufficiently without further modification. Therefore, we proposed and evaluated two new data imputation approaches to fill in the data gaps while approximating the shape of the original waveform in this study. These two approaches are Cubic Polynomial and Cubic Spline approximation.



(a) Raw siganture with issues (b) Signature with linear imputation

Figure 4. Raw signature and signatures with linear data imputation approach

A cubic polynomial is a polynomial function of degree three. The general cubic polynomial equation can be written as:

$$f(x) = a_3x^3 + a_2x^2 + a_1x + a_0 \tag{1}$$

Cubic spline approximation is a piecewise curve fitting method (Gerald and Wheatley, 1989). For the case with equal intervals, given the *i*th interval, the cubic function connects points and the function is defined by:

$$f = a_i(x - x_i)^3 + b_i(x - x_i)^2 + c_i(x - x_i) + d_i \tag{2}$$

where,

$$a_i = \frac{\Delta^2 f_{i+1} - \Delta^2 f_i}{6h},$$

$$b_i = \frac{\Delta^2 f_i}{2},$$

$$c_i = \frac{f_{i+1} - f_i}{h} - \frac{2h\Delta^2 f_i + h\Delta^2 f_{i+1}}{6}, \text{ and}$$

$$d_i = f_i.$$

The detailed comparison of these two approaches against the linear data imputation approach is illustrated in Figure 5. Figure 5 depicts a partial waveform in which only the first 0.1 seconds of the signature data are shown. It was found that the cubic polynomial and cubic spline approaches produced similar results. However, it was also found that the cubic polynomial approach showed oscillation in imputation results for very short time periods under certain scenarios (e.g., signatures collected from accelerating vehicles, as shown in Figure 6), which may generate unstable imputation results. On the contrary, the cubic spline approach produces smoother and more stable results than the cubic polynomial does. Figure 7 shows the resulting comparison of no data imputation, linear imputation, and cubic spline imputation. Therefore, the cubic spline data imputation approach was chosen to process the raw signature data in RTREID-2M.

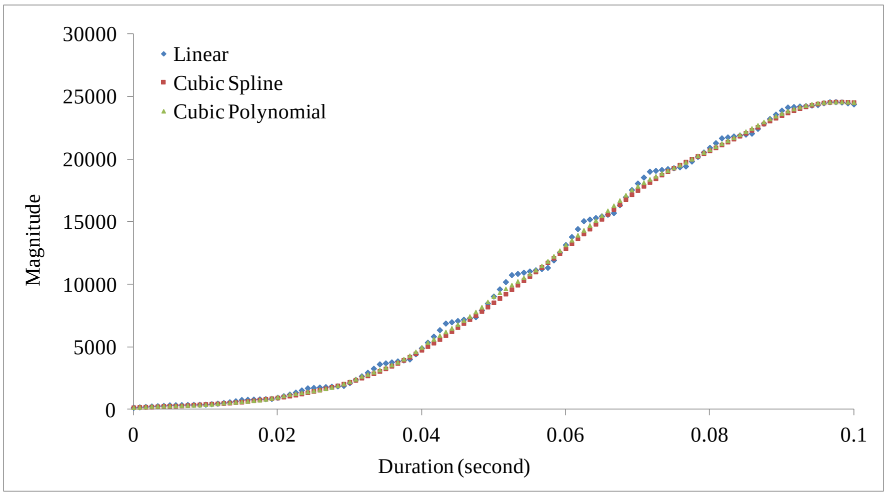


Figure 5. Linear imputation vs cubic polynomial imputation vs cubic spline imputation

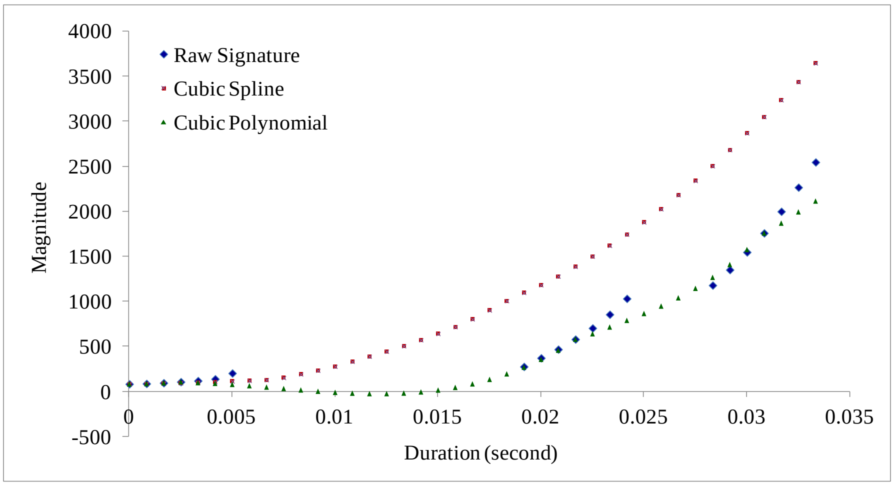


Figure 6. Detailed comparison of raw signature vs cubic polynomial imputation vs cubic spline imputation

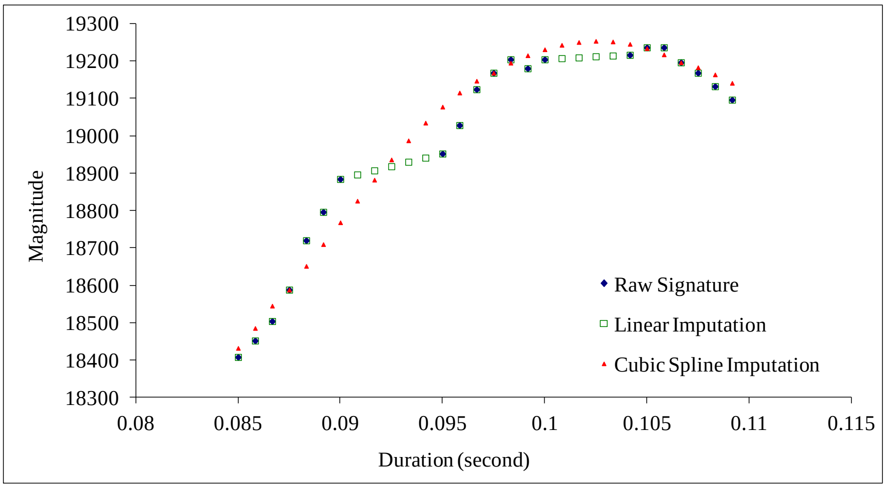


Figure 7. Comparison of raw signature vs linear imputation vs cubic spline imputation

3.2.2 Time Window Setting for Vehicles on HOV Lane

The time window restriction aims to determine a feasible and reasonable time period so that the correct vehicle can be included in the candidate vehicle set. The computational efficiency should be satisfied at the same time as well. Therefore, the estimated travel time is utilized to set up the lower and the upper bounds of the desired time window. The original RTREID-2 treats vehicles along mixed-flow lanes and HOV lanes the same. However, it was found that vehicles along HOV lane travel at free-flow speed for most of the time. In order to improve the performance of RTREID-2, the time window setting for vehicles from HOV lanes was modified so that the default lower boundary of the time window would be always applied.

The size of the time window can be described as follows:

```
If (HOV lane){
   time window lower bound = default lower boundary of the time window
   time window upper bound = estimated maximum travel time for HOV lane
}
else{    // general purpose lanes
   time window lower bound = estimated minimum travel time for non-HOV lanes
   time window upper bound = estimated maximum travel time for non-HOV lanes
}
```

With this modification, vehicles from HOV lanes traveling at free flow speeds will be considered when generating candidate vehicle sets even during congestion time periods. This modification is necessary to ensure that congestion observed on the mainline lanes, which is not usually replicated on the HOV lanes, does not interfere with matching vehicles traveling on HOV lanes.

4. STUDY SITE DESCRIPTIONS AND DATA PREPARATION

4.1 Study Site Descriptions

The study site is located on the Northbound I-405 freeway from Laguna Canyon Road to Sand Canyon Ave in Irvine, California. Loop detectors in a double configuration are available at both locations. Both stations are equipped with square loop detectors. Station 1 at Laguna Canyon Road overpass has seven lanes while Station 2 at Sand Canyon Ave overpass has six lanes. The study site configuration is displayed in Figure 8.

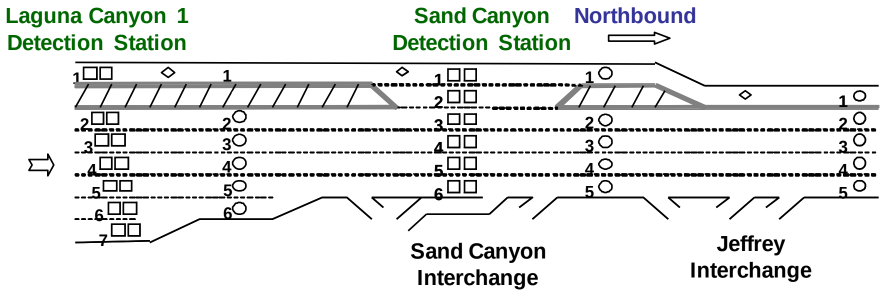


Figure 8. Study site: Northbound I-405 in Irvine, California

4.2 Data Preparation

4.2.1 Data Collection

The dataset used in this study was obtained from University of California, Irvine. The dataset was collected during the morning peak hours from 6:35AM to 10:00AM, May 12, 2009 and included both signature and video data captured from the field. The study time period covered the traffic conditions from free-flow to congestion and then back to free-flow. During congestion, the average travel speed was between 20 and 30 mph. In addition, it was found that the signature data for this dataset was of lower quality due to the noise present in the signatures as discussed in 3.2.1.

Partial ground-truthed data were available from this dataset. The ground-truthed data included nine discrete time periods: 6:35AM, 7:00AM, 7:35AM, 8:00AM, 8:10 AM, 8:20AM, 8:35AM, 9:00AM, and 9:35AM, in which three to five minutes of the video data was evaluated. Both uncongested (6:35AM, 7:00AM, 9:00AM, and 9:35AM) and congested (from 7:35AM to 8:35AM) traffic conditions were observed in the ground-truthed dataset. A total number of 4,827 vehicles were ground-truthed between stations.

4.2.2 Data Ground-truthing

In order to examine travel time performance, additional ground-truthed vehicles were required to show the changes of travel time over the whole time period. The obtained video data, which were captured in low-resolution, were used in generating more ground-truthed data. Ground-truthing was a very time consuming and labor intensive task, which involved manual checking and visual observation of the signature and video data. Therefore, a stratified-random sampling method was developed to effectively determine the number of vehicles required for estimating travel times at desired accuracy.

The objective of the stratified random sampling method approach was to determine the minimum number of vehicles that could be sampled such that the travel times computed from the sampled vehicles fell within a given range, or threshold, of the actual travel times. Each proposed sampling scheme below was firstly compared against the ground-truthed data obtained from UCI so that the sample size at each time interval (30 seconds) could be determined. The candidate sampling approaches include:

- Random 1: Randomly sample one vehicle
- Random 2: Randomly sample two vehicles
- Random 3: Randomly sample three vehicles
- Random 4: Randomly sample four vehicles
- Random 5: Randomly sample five vehicles
- Random 6: Randomly sample six vehicles

Next, an acceptable error percentage (i.e., threshold) of estimated travel time was defined. The approach that met the threshold was selected to perform the ground-truthing task later using the data between 7:15AM and 9:15AM, which captured the onset and the end of congestion.

The six proposed approaches were compared based on accuracy, and the one that provided the appropriate number of ground-truthed vehicles and the desired accuracy in travel time estimation was utilized in ground-truthing task. Three performance measurements were applied to evaluate the estimated travel time:

- Mean absolute percent error (MAPE)
- Kolmogorov-Smirnov (K-S) test
- Pearson's Correlation

It was noted that HOV lane vehicles should be considered separately from mainline vehicles as they usually had shorter travel times. Therefore, the proposed sampling method was only applied to non-HOV lane data.

4.2.3 Data Validation

The comparisons of the proposed approaches are listed from Table 1 to Table 3, and the performance for the congestion time period (8:00AM-9:00AM) is also evaluated. It is found that only the MAPEs of Random 1 exceed 2%. For the K-S test and Pearson's correlation, all of the proposed approaches yield similar performances.

Table 1. Comparisons of the proposed sampling approaches: MAPEs

MAPE Summary				
Sample Type	**Sample Size**	**Aggregation / Sample %**	**All Data**	**8-9am Only**
Random 1	71	1.7%	2.13%	2.14%
Random 2	142	3.4%	1.56%	1.44%
Random 3	213	5.1%	1.31%	1.34%
Random 4	284	6.8%	0.82%	0.89%
Random 5	355	8.5%	0.96%	0.75%
Random 6	426	10.2%	0.73%	0.62%

Table 2. Comparisons of the proposed sampling approaches: K-S test

K-S Test Dmax Summary (alpha = 0.05; Critical Value = Dc)				
Sample Type	**Sample Size**	**Aggregation / Sample %**	**All Data**	**8-9am Only**
			Dc = 0.16	Dc = 0.24
Random 1	71	1.7%	0.003	0.005
Random 2	142	3.4%	0.002	0.002
Random 3	213	5.1%	0.001	0.002
Random 4	284	6.8%	0.001	0.002
Random 5	355	8.5%	0.001	0.001
Random 6	426	10.2%	0.001	0.001

Table 3. Comparisons of the proposed sampling approaches: Pearson's Correlation

Pearson's Correlation Summary				
Sample Type	**Sample Size**	**Aggregation / Sample %**	**All Data**	**8-9am Only**
Random 1	71	1.7%	99.90%	99.69%
Random 2	142	3.4%	99.93%	99.79%
Random 3	213	5.1%	99.95%	99.86%
Random 4	284	6.8%	99.98%	99.94%
Random 5	355	8.5%	99.98%	99.96%
Random 6	426	10.2%	99.99%	99.97%

To facilitate the evaluation procedure, the results are further illustrated from Figure 9 to Figure 11. It can be seen from Figure 9 that the largest MAPEs are generated by the Random 1 approach. In general, the MAPEs for all the approaches are below 8%.

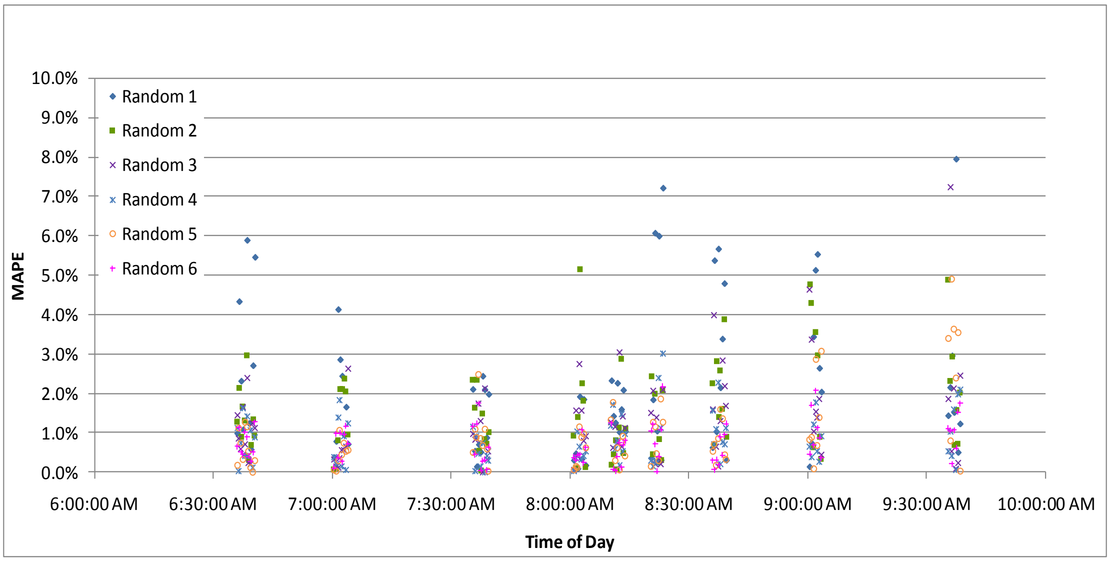
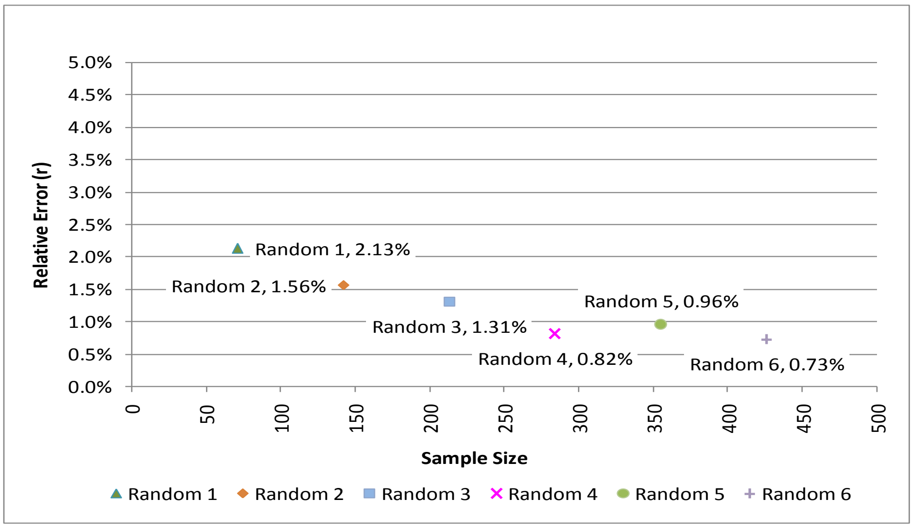
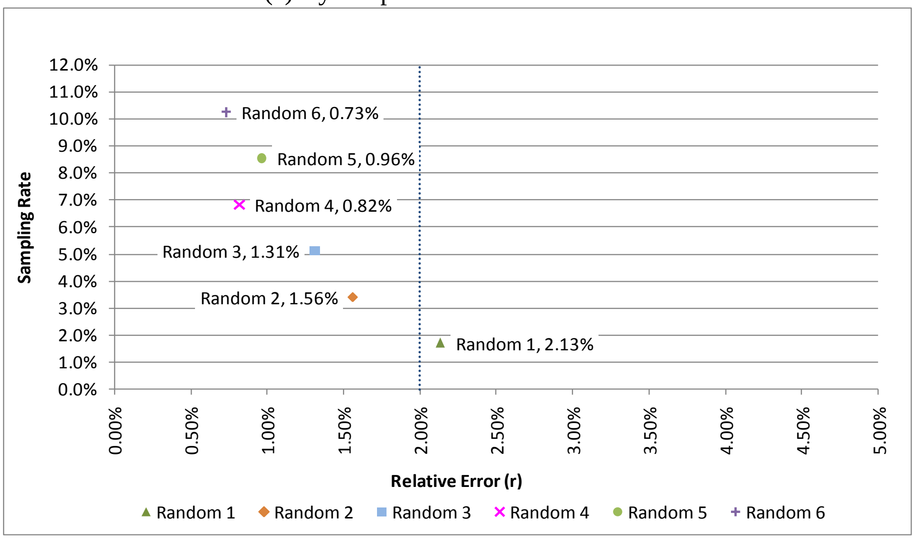


Figure 9. MAPEs: All data with 30-second aggregation



(a) By sample size and relative error



(b) By sampling rate and relative error

Figure 10. Random sampling results: All data with non-HOV lanes

It can be observed from Figure 10 that given the relative error below 2%, Random 2 approach requires the least amount of vehicles to achieve the goal. Moreover, with the sample size increasing from the Random 2 approach to the Random 6 approach (from 142 vehicles for Random 2 to 426 vehicles for Random 6), the relative error only decreases by 0.83% (from 1.56% to 0.73%). The benefit (% decreased in error) to cost (% increased in sample size) ratio is -0.27, which implies when the sample size is increased by 1%, the error will only decrease by 0.27%.

The resulting estimated travel times are shown in Figure 11 and no outlier is observed. Since the benefit of selecting the best performing approach, Random 6, was not significantly better than the approach requiring the least amount of additional ground-truthing, Random 2 was applied in the ground-truthing task. Based on the Random 2 sampling approach, data between 7:15AM and 9:15AM was divided into 30-second intervals. For each time interval, two vehicles were randomly selected for ground-truthing.

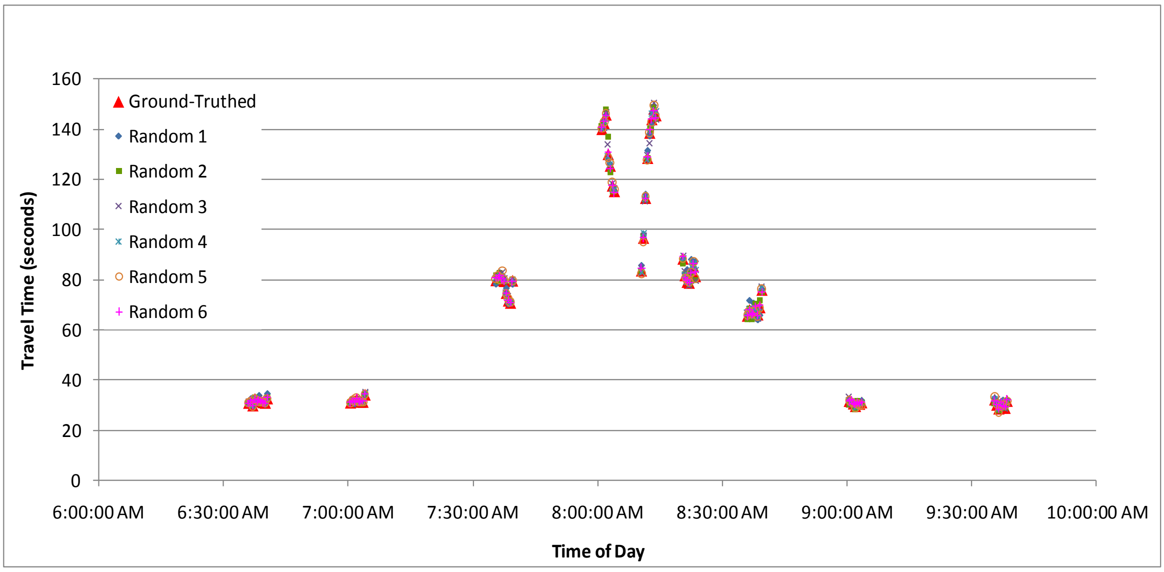


Figure 11. Estimated travel time: All data with 30s aggregation

In addition, all HOV lane vehicles from the same time period were ground-truthed. This was because less problematic signature data was observed on HOV lanes, and it was relatively easier to perform the ground-truthing task on HOV lanes (due to both limited lane changing and congestion). Upon completion of this task, an additional 2,706 vehicles representing the entire time period were added to the ground-truthed dataset.

5. PERFORMANCE EVALUATION

5.1 Reidentification Performance Evaluation

To evaluate the performance of RTREID-2M, three indices were applied, including total matching rate (TMR), system correct matching rate (SCMR), and mean absolute percent error (MAPE) of travel times:

$$\text{TMR} = \frac{\text{total number of matched vehicles}}{\text{total number of vehicles}} \tag{3}$$

$$\mathrm{SCMR} = \frac{\text{total number of correctly matched vehicles}}{\text{total number of matched vehicles}} \tag{4}$$

$$MAPE = \sum_{n=1}^{N}\left[\left|\frac{TTime_{obs,n} - TTime_{est,n}}{TTime_{obs,n}}\right| / N\right] \times 100\% \tag{5}$$

where,

$TTime_{obs,n}$: Observed average travel time at time step n (ground-truthed)

$TTime_{est,n}$: Estimated average travel time at time step n (reidentification algorithm)

N : Total number of time steps

The evaluation time period was from 6:30 to 10:00 AM. There were a total of 31,430 vehicles of which 4,827 vehicles at selected 3 to 5 min time periods were fully ground-truthed. For the whole study period, the total number of matched vehicles is 20,855 and the corresponding TMR is 66.4%. During the selected time periods, 3,224 vehicles of 4,827 vehicles are matched and the corresponding TMR is 66.8%. Table 4 shows the correct matching rate during each of the discrete ground-truthed time periods. The average SCMR is 65.6%. The SCMR is between 75% and 79% under the free flow condition and between 52% and 70% during congestion.

The actual numbers of correct matched vehicles are $4827 \times 66.8\% \times 65.6\% = 2115$, which corresponds to 43.8% of the total vehicles. According to related research (Oh and Jayakrishnan, 2002), 20% penetration rate of probe vehicles can be used to obtain the travel time data at enough accuracy.

Table 4. Reidentification performance for each ground-truth time period

Time period	**ALL**	**6:36:00 - 6:40:30**	**7:00:30 - 7:04:00**	**7:35:30 - 7:39:00**	**8:01:00 - 8:04:00**	**8:10:30 - 8:14:00**	**8:20:30 - 8:23:00**	**8:35:30 - 8:39:30**	**9:00:30 - 9:03:30**	**9:35:30 - 9:38:30**
SCMR	65.6%	74.5%	75.2%	51.8%	57.5%	70.1%	54.8%	55.3%	68.2%	78.7%

5.2 Travel Time Analysis

The results of the travel time accuracy evaluation are shown in Table 5. The MAPE of overall travel time performance (MAPE TT) is 4.3%. For free flow conditions, the average MAPE for each aggregation time interval is below 5%, equivalent to an accuracy of over 95%. For congestion time periods, the largest MAPE is 6.2%, indicating the accuracy is above 93%.

The proposed RTREID-2M was not able to match all vehicles. Even for those matched vehicles, some were incorrect matches. Their influence to travel time estimation was further quantified. First, the travel time performance was analyzed assuming all matched vehicles were correct matches (i.e., TMR = 66.8% and SCMR = 100%). This scenario represented the best condition the proposed approach could reach. All mismatched vehicles' records were found and then replaced with the ground-truth data. The evaluation results show that the MAPE of overall travel time performance is 2% if all 66.8% of vehicles are correctly matched.

Next, the travel time performance using only those mismatched vehicles was analyzed. This scenario indicated the worst condition the proposed approach could reach. As explained earlier, there were a total of 3,224 matched vehicles and 65.6% of them were correct matches. Therefore, there were 1,109 mismatched vehicles (equivalent to 23% of the total vehicles). The evaluation results show that the MAPE of overall travel time performance is 8.8% only using these mismatched vehicles' data.

For each time period, the travel time was calculated every 30 seconds. The selected results are shown in Figure 12. Figure 12**Error! Reference source not found.** illustrates the detailed comparisons between RTREID-2M and ground-truthed travel times via box-and-whisker plots for the time period from 8:20:30 to 8:23:00. The 30 second aggregated travel time is represented by the blue diamond for RTREID-2M and the pink square for the ground-truthed data. The box-and-whisker plots include some useful information about the ground-truthed data.

It is found that for all of the ground-truthed time periods, RTREID-2M produces highly accurate travel time results and matches the ground-truthed travel times quite well. All of the RTREID-2M travel times fall within one standard deviation of the mean ground-truthed travel times except for two time periods (7:04:00 and 8:39:30).

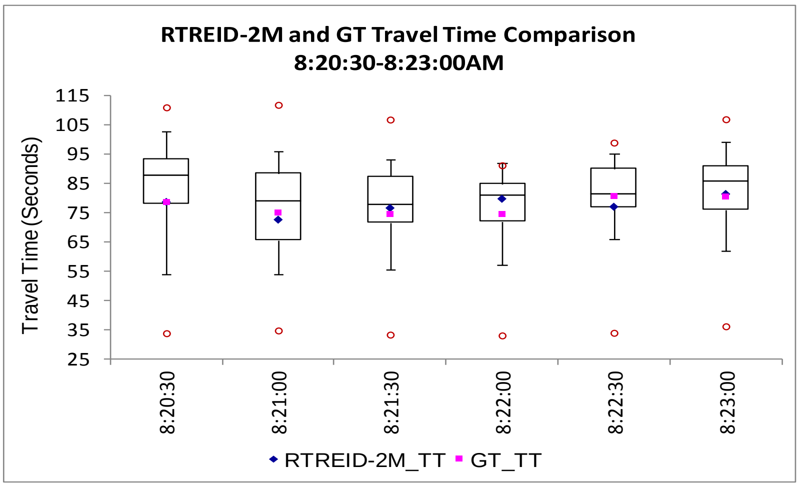
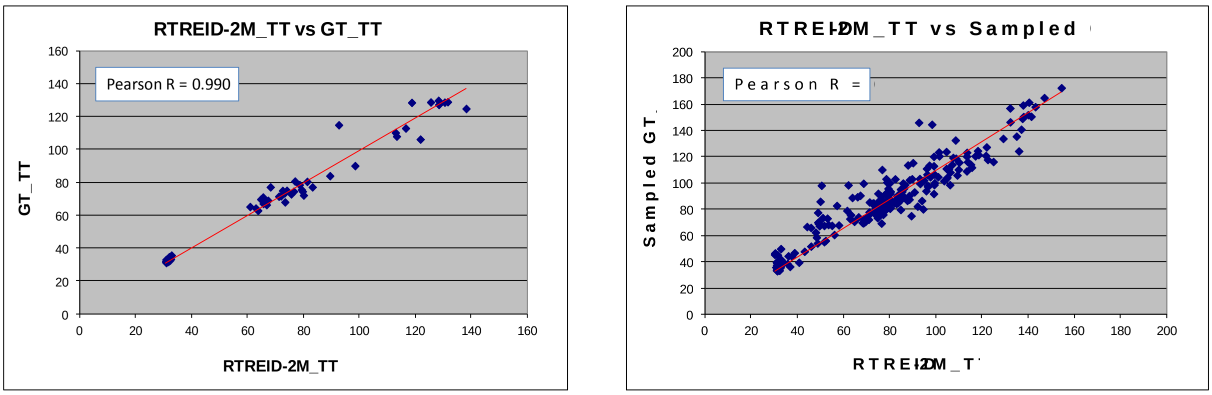


Figure 12. RTREID-2M travel times vs ground-truthed travel times: 8:20:30-8:23:00AM

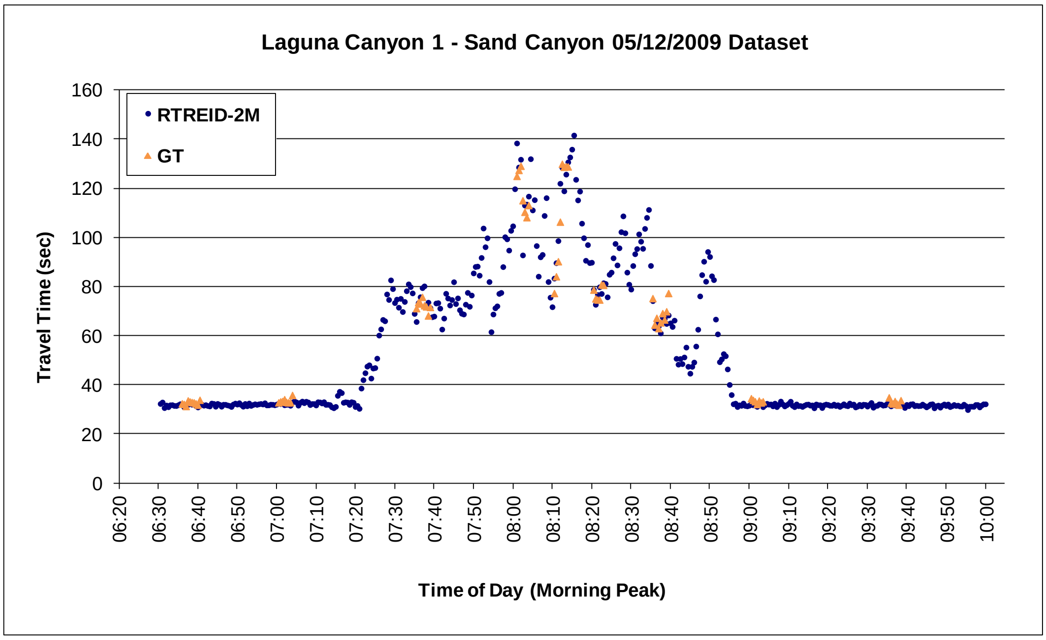
The correlation between RTREID-2M and ground-truthed travel times is also examined as shown in Figure 13(a). The high Pearson R value (i.e., 0.990) indicates the good matches of the trends of the travel times over time. Furthermore, since the ground-truthed dataset does not cover the whole time period of data, the sampled ground-truthed travel times described in 4.2.3 are utilized to show the performance of the RTREID-2M travel time. Figure 13(b) shows strong correlations between RTREID-2M and sampled ground-truthed travel times with the high Pearson R value, 0.955.



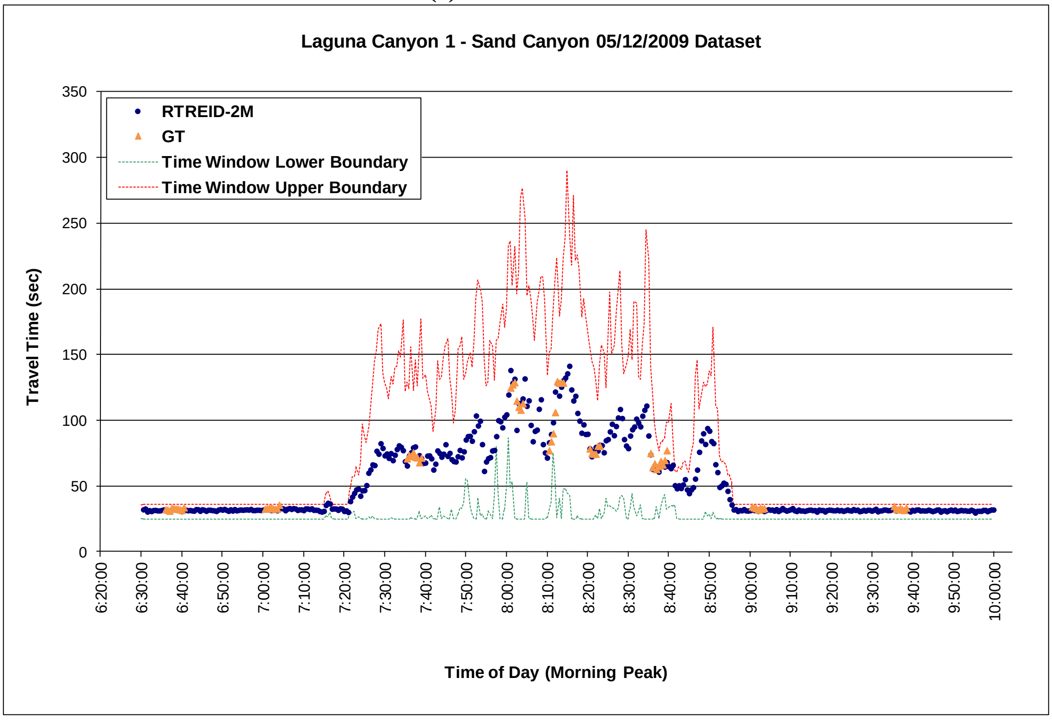
(a) RTREID-2M vs ground-truthed travel times (b) RTREID-2M vs sampled ground-truthed travel times

Figure 13. Pearson R analysis

In addition, as shown in Figure 14(a), the RTREID-2M travel times follow the trend of the actual travel times very closely. The time window, which is one of the most important parameters in RTREID-2M, is dynamically changed based on traffic conditions as shown in Figure 14(b), which illustrates the upper and lower boundaries of the time window. Since the study site has both mixed-flow lanes and HOV lane facilities, the time window is big enough to include all the potential candidate vehicles.



(a) 6:30-10:00AM



(b) With time window boundaries

Figure 14. RTREID-2M travel times vs ground-truthed travel times

The RTREID-2M travel times generally follow the trend of the sampled ground-truthed travel times very well during the congestion period as shown in Figure 15. Comparing with the sampled travel time, the overall MAPE of RTREID-2M travel time is 12.1%. Figure 16 compares the section travel speed estimated by RTREID-2M against the ground-truthed travel speed and the point speeds estimated using volume and duration data extracted from the raw signature data. It can be observed that RTREID-2M speed estimates are very accurate whereas point speeds are not reliable measurements of section travel speed.

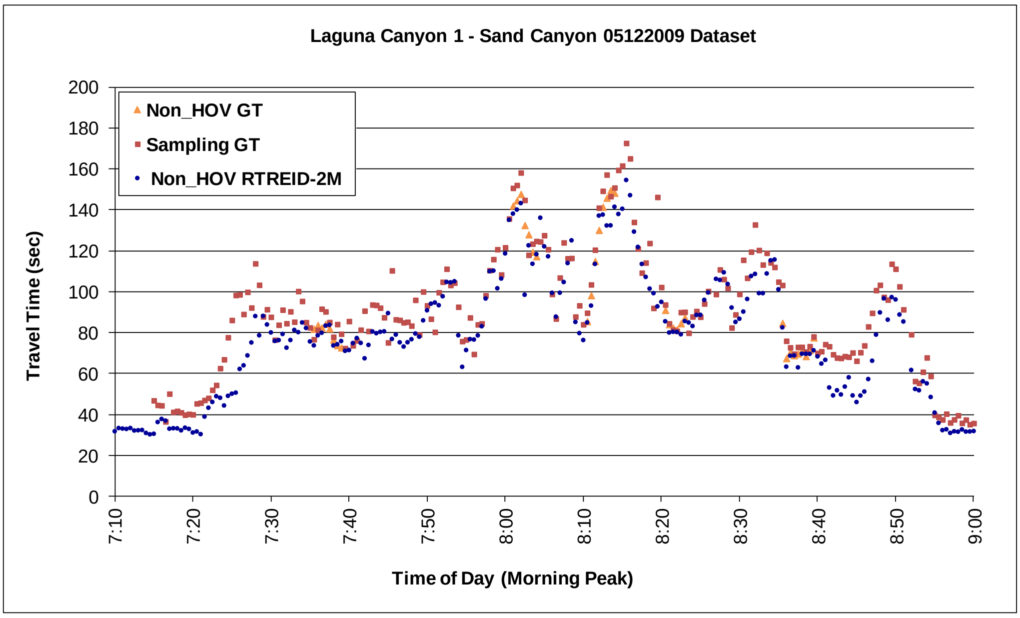


Figure 15. RTREID-2M travel times vs sampled ground-truthed travel times: congestion period

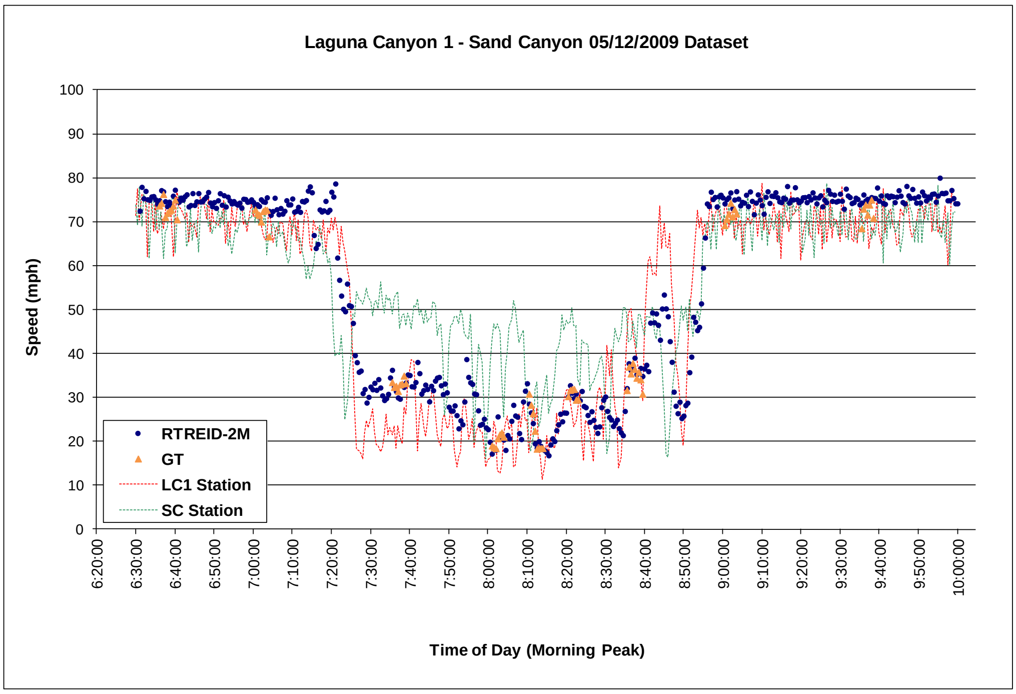


Figure 16. RTREID-2M speeds vs point speeds vs ground-truthed speeds

As indicated earlier, point detector speed is not representative of section travel speed. However, the point speeds are widely used in the estimation of section travel time. Therefore, two methods of section travel time estimations using point speeds were analyzed and compared in this study:

- Section travel time by average speed:

$$\text{TT by Average Speed} = \frac{\text{distance}}{\left(\frac{\text{upstream point speed} + \text{downstream point speed}}{2}\right)} \tag{6}$$

- Section travel time by weighted distance:

$$\text{TT by Weighted Distance} = \frac{\text{distance}}{\text{upstream point speed}} \times 0.5 + \frac{\text{distance}}{\text{downstream point speed}} \times 0.5 \tag{7}$$

As shown in Figure 17, both point detector based travel time methods have limited capabilities of computing accurate section travel time compared to RTREID-2M. For instance, the point estimates dramatically drop from 8:00AM to 8:10A, whereas RTREID-2M does not.

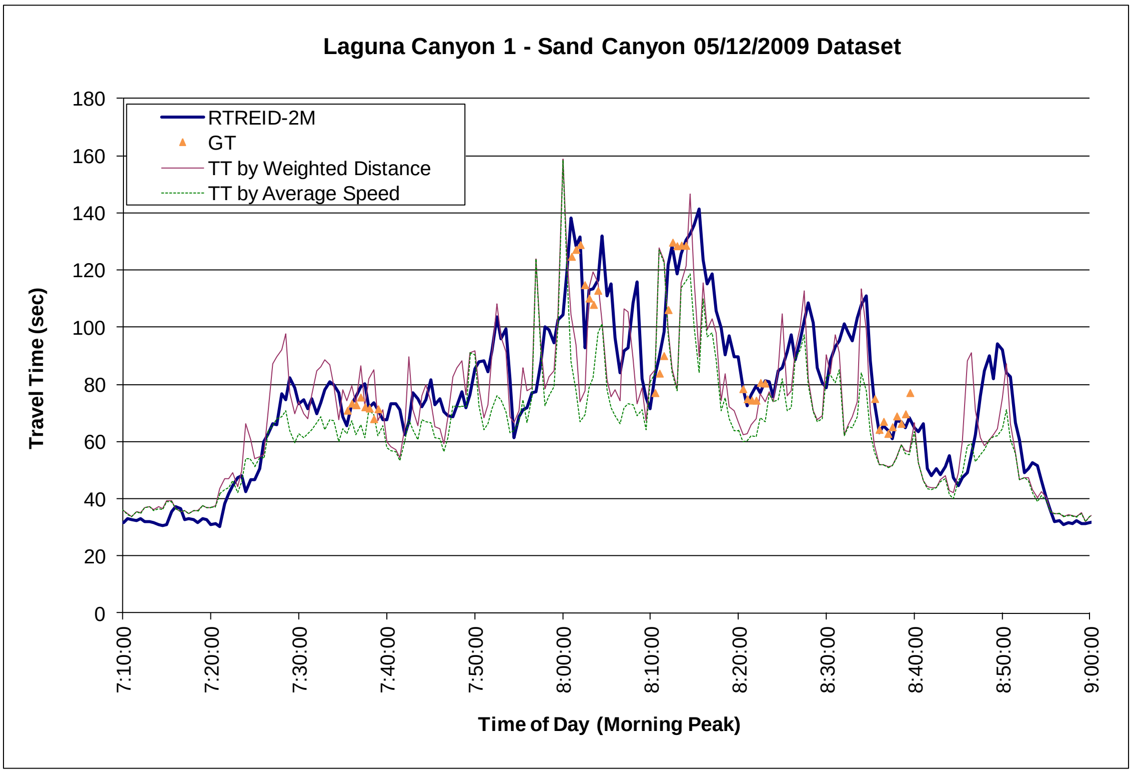


Figure 17. Comparisons of travel times: Congestion Period

6. CONCLUSIONS AND FUTURE RESEARCH

In this study, a real-time inductive loop signature based vehicle reidentification approach, named RTREID-2M, was proposed and evaluated. This research was conducted based on the existing knowledge and the latest academic research product, RTREID-2. The inductive signature technology was introduced and the research basis for the application of the technology was explained. The proposed RTREID-2M improved the original RTREID-2 on two aspects: (1) The cubic spline data imputation approach was developed to replace the existing linear data imputation approach in order to improve the quality of the raw signature data; (2) The time window setting for vehicles on HOV lanes was modified so that vehicles on HOV lanes traveling with free flow speeds would be considered when generating candidate vehicle sets even during congestion time periods. Additionally, a stratified-random sampling method was developed to effectively perform grouth-truthing task for showing the changes of travel time over the whole time period.

The results obtained from this study showed desired performance for vehicle reidentification and travel time estimation under both free-flow and congested flow traffic conditions. The system correct matching rate (SCMR) was between 75% and 79% under the free-flow condition and between 52% and 70% during congestion. The accuracy of overall travel time performance was over 95%. The strong correlation (Pearson R = 0.955) between RTREID-2M and ground-truthed travel times indicated the good matches of the trends of the travel times over time. Furthermore, the travel times obtained from RTREID-2M were compared with the travel times estimated via two point detector based travel time methods using point speeds, which were widely used in the estimation of section travel time. The results demonstrated that both point detector based methods had limited capabilities of providing accurate section travel times compared to RTREID-2M. The future researches will focus on the potential applications and arterial vehicle reidentification utilizing the inductive loop signature technology.

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8. REFERENCES

Abdulhai, B., Tabib, S. (2003) Spatio-temporal inductance-pattern recognition for vehicle re-identification. *Transportation Research*, 11C(3), 223-239.

Coifman, B., Kim, S. (2009) Speed estimation and length based vehicle classification from freeway single loop detectors. *Transportation Research*, 17C(4), 349-364.

Gajda, J., Sroka, R., Stencel, M., Wajda, A., Zeglen, T. (2001) A vehicle classification based on inductive loop detectors. In *Proceeding of the 18th IEEE Instrumentation and Measurement Technology Conference*, Vol. 1, 460-464, Budapest, Hungary.

Gerald, C. F., Wheatley, P. O. (1989) *Applied Numerical Analysis*. Addison-Wesley Publishing Company, Reading, MA.

Jeng, S.-T., Chu, L., Hernandez, S. (2012) A Vehicle classification approach based on wavelet k-nearest neighbor using inductive loop signatures. *Proceedings of the 92th Annual Meeting of the Transportation Research Board*, 13-3182, Washington, D.C.

Jeng, S.-T., Ritchie, S. G. (2006) A new inductive signature data compression and transformation method for on-line vehicle reidentification. *Proceedings of the 85th Annual Meeting of the Transportation Research Board*, 06-3068, Washington, D.C.

Jeng, S.-T., Ritchie, S. G. (2008) Real-time vehicle classification using inductive loop signature data. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2086, 8-22.

Jeng, S.-T., Tok, A., Ritchie, S. G. (2010) Freeway performance measurements based on vehicle reidentification. *IEEE Transactions on Intelligent Transportation Systems*, 11(3), 639-646.

Ki, Y., Bai, D. (2005) Vehicle classification model for loop detectors using neural networks. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1917, 164-172.

Kwon, T., Parsekar, A. (2006) Blind deconvolution processing of loop inductance signals for vehicle reidentification. *Proceedings of the 85th Annual Meeting of the Transportation Research Board*, 06-2581, Washington, D.C.

Ndoye, M., Totten, V., Carter, B., Bullock, D., Krogmeier, J. (2008) Vehicle detector signature processing and vehicle reidentification for travel time estimation. *Proceedings of the 87th Annual Meeting of the Transportation Research Board*, 08-0497, Washington, D.C.

Oh, C., Ritchie, S. G. (2002) Real-time inductive-signature-based level of service for signalized intersections. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1802, 97-104.

Oh, C., Ritchie, S. G. (2005) Development of methodology to design advanced traffic surveillance systems for traffic information based on origin-destination. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1935, 37-46.

Oh, C., Tok, A., Ritchie, S. G. (2005) Real-time freeway level of service using inductive-signature-based vehicle reidentification system. *IEEE Transactions on Intelligent Transportation Systems*, 6(2), 138-146.

Oh, J.-S., Jayakrishnan, R. (2002) Emergence of private advanced traveler information service providers and their effect on traffic network performance. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1783, 167-177.

Sun, C., Ritchie, S. G., Tsai, K., Jayakrishnan, R. (1999) Use of vehicle signature analysis and lexicographic optimization for vehicle reidentification on freeways. *Transportation Research*, 7C(4), 167-185.

Sun, C., Ritchie, S. G., Oh, S. (2003) Inductive classifying artificial network for vehicle type categorization. *Computer Aided Civil and Infrastructure Engineering*, Vol. 18, 161-172.

Tawfik, A. Y., Abdulhai, B., Peng, A., Tabib, S. M. (2004) Using decision trees to improve the accuracy of vehicle reidentification. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1886, 24-33.

Tok, A., Jeng., S.-T., Liu, H., Ritchie, S. G. (2008) Design and initial implementation of an inductive signature-based real-time traffic performance measurement system. *Proceedings of the 11th International IEEE Conference on Intelligent Transportation Systems*, 216-221, Beijing, China.

Wang, Y., Nihan, N. L. (2003) Can single loop detectors do the work of dual loop detectors? *ASCE Journal of Transportation Engineering*, 29(2), 169-176.

Zhang, G., Wang, Y., Wei, H. (2006) Artificial neural network method for length based vehicle classification using single-loop outputs. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1945, 100-108.