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Real-time Inductive-Signature-Based Level of Service for Signalized Intersections

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ABSTRACT

The U.S. Highway Capacity Manual (HCM) presents a procedure for estimating signalized intersection control delay, which is used to determine Level Of Service (LOS) and to evaluate intersection performance. The HCM is used extensively by traffic engineers. However, it is intended as an off-line decision support tool for planning and design. To meet user requirements of Advanced Traffic Management Systems (ATMS), new LOS criteria are required for real-time intersection analysis. The objective of this research was to demonstrate a technique for development of such LOS criteria. The study uses a new measure of effectiveness, called Re-identification Delay (RD) derived from analysis of vehicle inductive signatures and reidentification of vehicles traveling through a major signalized intersection in the City of Irvine, California.

This paper tackles two main issues regarding real-time LOS criteria. The first is how to determine the threshold values partitioning the LOS categories. To provide reliable real-time traffic information, the threshold values should be decided so that RDs within the same LOS category should represent similar traffic conditions as much as possible. On the other hand, RDs in different LOS categories should also represent dissimilar traffic conditions. The second issue concerns the aggregation interval to use for RD in deriving LOS categories. An investigation of both fixed and cycle-based aggregation intervals was conducted. Several clustering techniques were then employed to derive LOS categories, including K-means, Fuzzy, and Self-Organizing Map (SOM) approaches. The resulting real-time LOS criteria are presented. The procedures used in this study are readily transferable to other signalized intersections for the derivation of real-time LOS.

INTRODUCTION AND RESEARCH BACKGROUND

The U.S. Highway Capacity Manual (HCM) (1) presents a procedure for estimating control delay, which is used to determine Level Of Service (LOS) and to evaluate intersection performance. The HCM is used extensively by traffic engineers. However, it is intended as an off-line decision support tool for planning and design. To meet user requirements of Advanced Traffic Management Systems (ATMS), new LOS criteria are required for real-time intersection analysis. The objective of this research was to demonstrate a technique for development of such LOS criteria. The study uses a new measure of effectiveness, called Re-identification Delay (RD) derived from analysis of vehicle inductive signatures and reidentification of vehicles traveling through a major signalized intersection in the City of Irvine, California. RD is defined as the difference between the actual time required to traverse vehicle reidentification stations at a signalized intersection and a base travel time such as that calculated from the speed limit. The availability of real-time LOS is of considerable value to operating agencies interested in congestion monitoring, real-time control, incident detection, provision of real-time traveler information, and system evaluation.

LOS is a key concept for evaluating the operational quality of transportation systems. The HCM LOS criteria for traffic signals are stated in terms of the average control delay per vehicle, typically for a 15-min analysis period. With the capability to obtain RD from a vehicle reidentification system, the possibility of obtaining new LOS criteria that can be used for real-time intersection analysis emerges. Two viewpoints can also be considered for the purpose of real-time intersection analysis. Firstly, operating agencies need to obtain real-time traffic conditions in order to control and manage traffic systems. Secondly, drivers or users of the traffic system require high quality and reliable traffic information to decide their route choice in real-time.

Several studies have been performed relating to the derivation of LOS criteria. As expansions of the existing HCM A-F criteria for increasing urban traffic congestion, Cameron (2) and Baumgaertner (3) proposed extending the LOS criteria from A to J and A to I, respectively. Their concern was that longer delay due to increasing congestion was common. Therefore, criteria representing traffic conditions beyond LOS F were proposed by adding extra categories somewhat arbitrarily. Sutaria *et al*. (4) examined user perceptions of LOS based on user-rating data collected at a signalized intersection. More recently, Pecheux *et al*. (5) presented preliminary analyses about how users perceive level of service and how many levels of service are perceived. The result indicated that two or three levels of service were generally perceived. Madanat *et al*. (6) applied an ordered probit model to determine thresholds for each category for transit LOS using bus rider attitudinal data and based on the existing six levels (A-F) in the HCM. With a different view, Ha and Berg (7) developed safety based LOS criteria using conflict opportunity models that were derived for crossing, diverging, and stopping maneuvers associated with left-turn and rear-end accidents. Saito *et al*, (8) developed a multilayer artificial neural network (ANN) based LOS evaluation model using the same criteria as in the HCM. Their model used delay data from the Highway Capacity Software (HCS) (9). As the authors mentioned, if one has a capability to obtain delay directly in the field, we can achieve a higher accuracy of LOS. From this brief review of existing studies, it appears that no study has attempted to develop real-time LOS criteria.

This paper is primarily focused on two issues. The first issue is how to determine the threshold values for partitioning different LOS categories. To provide reliable real-time information, the threshold values should be decided such that RDs within the same category represent similar traffic conditions as much as possible. On the other hand, RDs in different LOS categories should also represent dissimilar traffic conditions. The second issue concerns the aggregation interval to use for RD in deriving LOS categories. An investigation of both fixed and cycle-based aggregation intervals is conducted. Several clustering techniques are then employed to derive LOS categories, including K-means, Fuzzy, and Self-Organizing Map (SOM) approaches.

In this paper, we present new LOS criteria that can be used for providing both operating agencies and drivers with traveler information and for evaluating real-time intersection performance. The paper discusses a real-time intersection surveillance system, aggregation issues, determination of LOS criteria based on clustering analysis, and our conclusions.

REAL-TIME INTERSECTION SURVEILLANCE SYSTEM BASED ON VEHICLE REIDENTIFICATION

A real-time traffic surveillance system based on vehicle inductive signatures and vehicle reidentification has been implemented in the City of Irvine, California. The intersection of Alton Parkway and Irvine Center Drive (Alton/ICD) is an eight phase fully actuated intersection where each approach has a set of double loop detectors, referred to as approach detectors. These detectors are about 325 ~ 375 feet upstream from the intersection stop line, except for the eastbound Alton loops which are 800 feet from the intersection. Additionally, there are downstream double loop detectors in each lane right after the intersection; these are referred to as downstream detectors in this study. This brings the total number of loops at the intersection to 48, as shown in Figure 1. Some of these loops were pre-existing at the intersection (for an adaptive signal control study) and some were specially installed for this project. In the future, the city is interested in installing single loops upstream on each link for adaptive control purposes. Our ongoing research will seek to utilize existing sensors and detectors rather than specially installed ones, as in this study.

Vehicle signature data are extracted in real-time by high-speed scanning loop detector cards and stored in a dedicated computer at the Irvine Transportation Center (ITC). These data can be accessed at the Irvine Transportation Management Center (TMC) via a Local Area Network (LAN). A new Wide Area Network (WAN) will also enable transmission of data to the University of California, Irvine (UCI). Because of current hardware limitations, vehicle signature data from only one upstream site (Alton Parkway eastbound) and its corresponding three downstreams are collected in real-time.

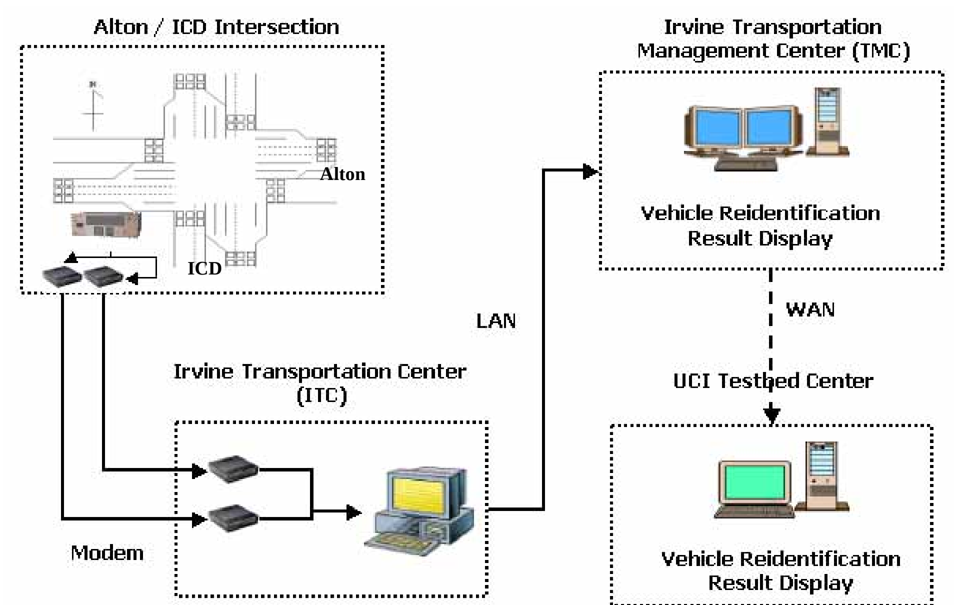
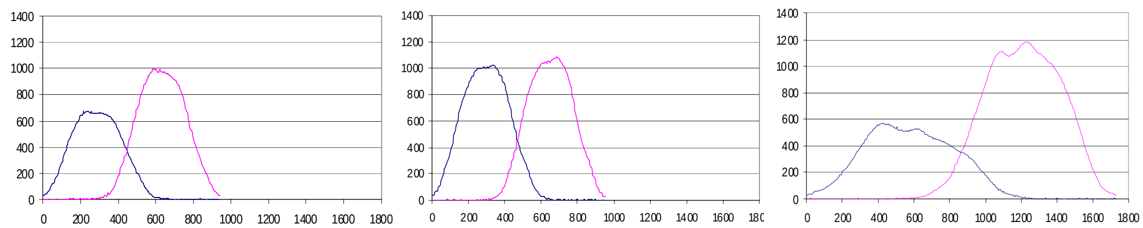


Figure 1 Study intersection and data communication

Applying the concept of the lexicographic method developed by Sun et al. (10) for a freeway application, vehicle reidentification was formulated as a five-level optimization problem. Minimizing mismatches between feature vector pairs denotes the "optimization" on any given objective. However, unlike the freeway case, the intersection study site is interrupted by vehicle-actuated signal control, resulting in highly variable travel times. Each downstream station also has three different upstream stations. In this application, signal phase information was not available so, overall, the optimization was much more challenging. Because of this, an optimization level to filter individual vehicle turning movements was added to identify the upstream origin of each vehicle. This routine of the reidentification process contributes to faster algorithm running times and to improving the matching rate of individual vehicles. Intersection turning movement estimation is also directly related to the Origin/Destination (OD) matrix at the intersection.

To classify turning movements, heuristic algorithms were developed and embedded in the reidentification system. Three main downstream features, inductive signature maximum magnitude difference between the front and back loops in each lane (max_mag), vehicle speed, and lane information, were used in these algorithms. The maximum magnitude of the signature relates to vehicle height as the magnitude is generated according to the vertical distance of the vehicle from the loop. Figure 2 shows some characteristics of typical signatures for each movement that were observed at the downstream loop detectors. The vertical axis in each case is proportional to the change in inductance, and the horizontal axis represents time (in milliseconds). Figure 3 shows the overall vehicle reidentification algorithm. Further details are discussed by Ritchie *et al*. (11).



(a) Left-turn signature (b) Through signature (c) Right-turn signature

Figure 2 Downstream vehicle signatures for each movement at the study intersection

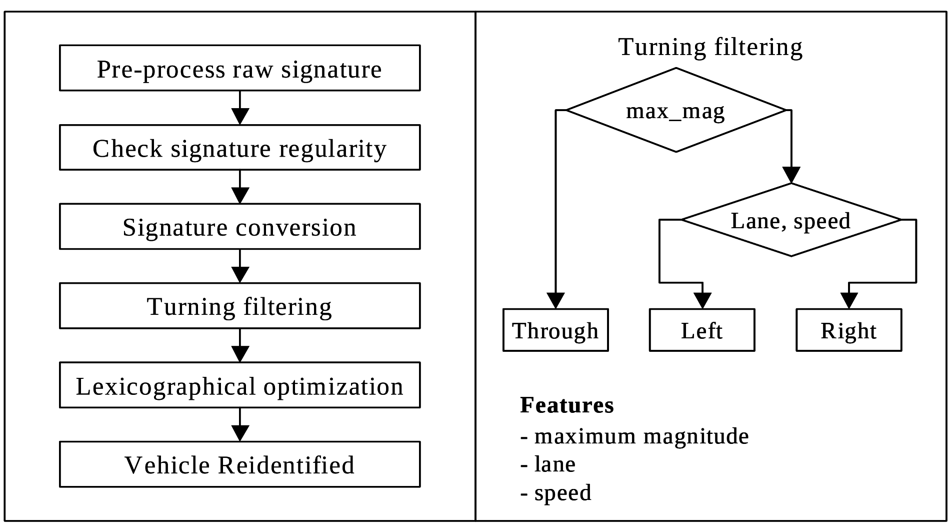


Figure 3 Intersection Vehicle Reidentification Flow Chart

Data were collected on August 16, 2000 during an AM non-peak hour from 9:30 AM to 11:00 AM. Data were recorded only for upstream Alton Parkway eastbound and the corresponding three downstream locations. The upstream data contained approximately 740 vehicles. Table 1 summarizes the vehicle reidentification performance for this data set in terms of correctly matched upstream vehicles. All those vehicles matched by the vehicle reidentification system were used to determine real-time LOS.

Table 1. Performance of Vehicle Reidentification Technology

	Through	Right	Left	Overall
Matching Rate (%)	51.7	32.5	62.5	46.7

A differenece between RD and control delay, which is used as the basis of LOS in the HCM, exists due to the loop configuration of our instrumented intersection. Figure 4 shows the definition of RD and control delay with the associated time-distance relationship for a specific vehicle. As identified in Figure 4, RD and control delay can be expressed as follows (in order to compute RD we used the speed limit 55mph).

$$* \mathrm{RD} = (t_6 - t_1) - (\frac{l_6 - l_1}{V_o})$$

$$* \mathrm{Control\ Delay} = (t_7 - t_2) - (\frac{l_7 - l_2}{V_o})$$

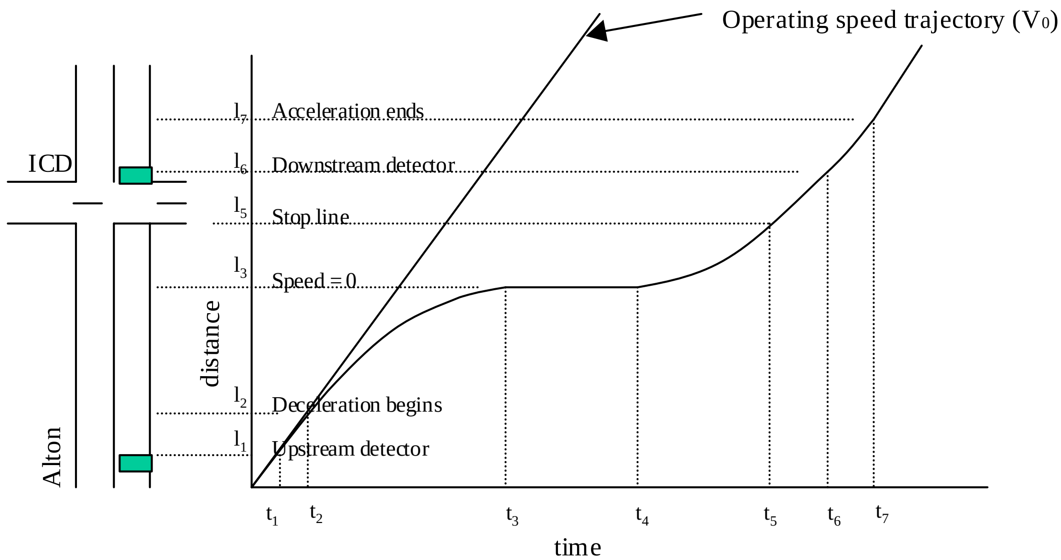


Figure 4 Schematic time-distance diagram depicting RD and control delay

METHODOLOGY FOR DETERMINING LOS CRITERIA

The threshold values used to partition LOS designations should effectively reflect real-time traffic conditions in each category. This partitioning should have the following properties: homogeneity of RD within the same categories, i.e. data that belong to the same category should be as similar as possible, and heterogeneity of RD between categories, i.e. data belonging to different categories should be as different as possible. A solution that can satisfy the above two constraints can be obtained by the formulation of two maximization problems: first to maximize dissimilarity between categories, and second to maximize similarity within categories. Consistent with this, we have applied clustering algorithms to determine the “optimal” number of categories in a given data set. Cluster analysis is different from classification in that no assumptions are made concerning the number of groups. The aim of the cluster analysis is to partition a given set of data or objects into clusters. We investigated K-means clustering, Fuzzy clustering, and an artificial neural network Self-Organizing Map (SOM).

For clustering analysis, the time taken by individual vehicles passing between upstream and downstream detectors corresponds to RD and is an output of our surveillance system. Two time periods representing a range of traffic conditions at the study intersection were selected by field investigation of daily traffic patterns. One data collection period was from 09:30 to 11:20 am, which represents off peak traffic conditions. The other was from 5:00 to 6:00 pm, which represents peak hour traffic conditions. The clustering methodologies were only applied to through and right turn movements due to a lack of left turn data. The collected data are summarized in Table 2.

Table 2 Collected data for clustering analysis

Data	Through vehicles	Left vehicles	Right vehicles	Total vehicles*
09:30 ~ 11:20	370	9	149	528
17:00 ~ 18:00	438	18	283	739

* at upstream Alton Parkway eastbound station

In addition, RDs, were aggregated into short time intervals, so that the average RD in each period could serve as the basis of the cluster analysis. Two different aggregation methods were investigated: a cycle-length based average (CBA) and a fixed time average (FTA). Because cycle lengths are constantly varying, an on-line algorithm was written to identify the start and end of each cycle. For comparison, a fixed interval of 60 seconds was used for FTA analysis. Figure 5 shows a comparison of the two approaches.

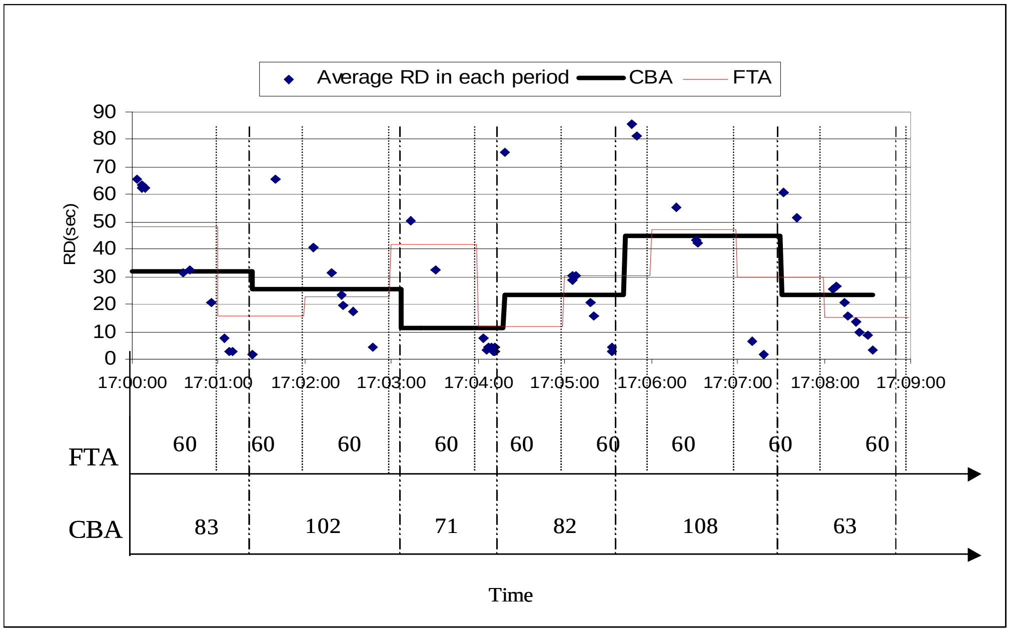


Figure 5 Average travel times for different aggregation methods (CBA vs. FTA) for through vehicles

K-means clustering

K-means clustering is one of the most well known partitioning methods (12). The algorithm computes k representative objects called medoids, which together determine a clustering. The number k of clusters is an argument of the function. Each object is then assigned to the cluster corresponding to the nearest medoid. That is object i is put into cluster v_i when medoid m_{v_i} is near than any other medoid m_w:

$d(i, m_{v_i}) \le d(i, m_w)$ for all $w = 1, ..., k$

The k representative objects should minimize the sum of the dissimilarities ($d(i,m)$) of all objects to their nearest medoid:

$$\text{objective function} = \sum_{i=1}^{n} d(i, m_{v_i})$$

Fuzzy Clustering

Unlike conventional crisp clustering, such as K-means where each object of the data set is assigned to exactly one cluster, each observation in fuzzy clustering is given fractional membership in multiple clusters. For each object i and each cluster v, there will be a membership u_{iv} which indicates how strongly object i belongs to cluster v. Memberships have to satisfy the following conditions (13):

$$u_{iv} \geq 0 \quad \text{for all } i = 1,....,n \text{ and all } v = 1,......,k$$

$$\sum_{v=1}^{k} u_{iv} = 1 = 100\% \quad \text{for all } i = 1,......,n$$

The memberships are defined through minimization (12) of:

$$\text{objective function} = \sum_{v=1}^{k} \frac{\sum_{i,j=1}^{n} u_{iv}^2 v_{jv}^2 d(i,j)}{2\sum_{j=1}^{n} u_{jv}^2}$$

In this expression, the dissimilarities $d(i,j)$ are known and the membership u_{iv} are unknown. The minimization is carried out numerically by an iterative algorithm, taking into account the above conditions that membership need to obey. The result of fuzzy clustering can be shown as crisp clusters by assigning each object i to the cluster v in which it has the highest membership u_{iv}.

Self Organizing Map

The SOM developed by Kohonen is two-layer neural network that falls into the category of unsupervised learning methodology for clustering and dimension reduction. An advantage of SOM over other clustering algorithms is its ability to visualize high dimensional data using a two-dimensional grid while preserving similarity between data points as much as possible (14). The observations are automatically organized into a meaningful two-dimensional order in which similar ones are closer to each other in the grid than the more dissimilar ones. In this sense the SOM can be regarded as a multivariate clustering algorithm to seek clusters in the data.

Each node of the SOM contains a weight vector, which is equal to the dimension of the feature vectors. Originally, the weight vectors are initialized to random values. During the training, the weight vectors are modified based on the input feature vectors according to the following two steps.

<u>Step1</u>: Search winning node

When each input x is entered into the Kohonen layer, the neurons compute the input intensity $I_j = D(\underline{w}_j, \underline{x})$, where $D(\underline{w}_j, \underline{x})$ is a distance measurement function, in which Euclidean distance is commonly used. After each neuron calculates its I_j, a 'competition' occurs to find the neuron called 'winner' with smallest I_j.

<u>Step2</u>: Update weight

When the winning neuron c is determined, the weight vectors w are updated according to the following rule:

$$\underline{w}_j^{new} = \begin{cases} \underline{w}_j^{old} + \alpha[\underline{x} - \underline{w}_j^{old}], & j \in N_c \\ \underline{w}_j^{old}, & \text{otherwise} \end{cases}$$

Here N_c is the neighborhood of the winner node c, and α is the learning coefficient. Both are decreasing with time during the training. Step 1 and 2 are repeated until the map has converged, which may be tested using average quantization error of training vectors. As a result of this learning algorithm, the clusters corresponding to characteristic features are formed onto the map automatically. Although SOM identifies a winning neuron based on the same method as employed by traditional competitive learning, it differs from competitive learning in that all neurons within a certain neighborhood of the winning neuron are adjusted instead of adjusting only the winning neurons. After the map has been organized, the clusters can be labeled, which is corresponding to a physical interpretation of the formed clusters.

Clustering Results

To compare the results of each clustering methodology, we used Wilk's lambda (Λ) defined as the ratio of within-groups variance to total variance. A lower Wilk's lambda represents better clustering (15).

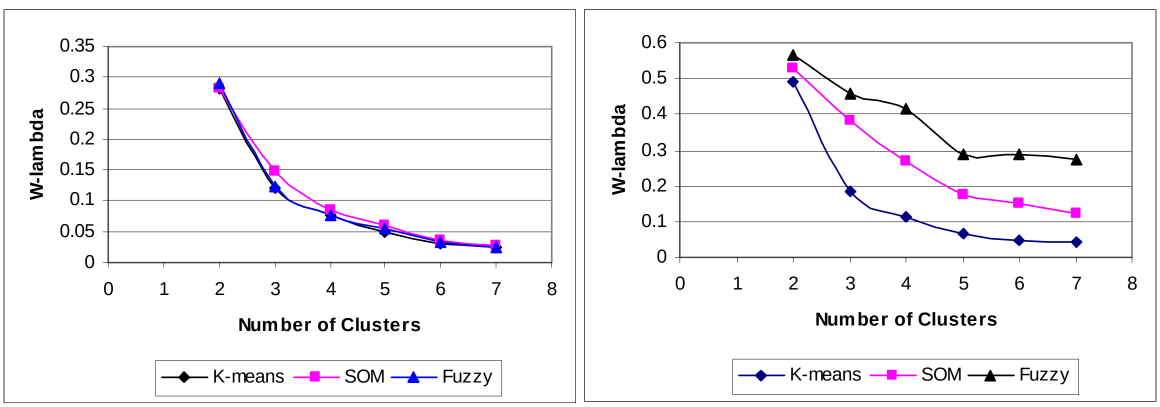
$$\Lambda = \frac{|W|}{|T|} = \frac{|W|}{|B+W|}$$

where, W = pooled within-groups variance

B = between groups variance

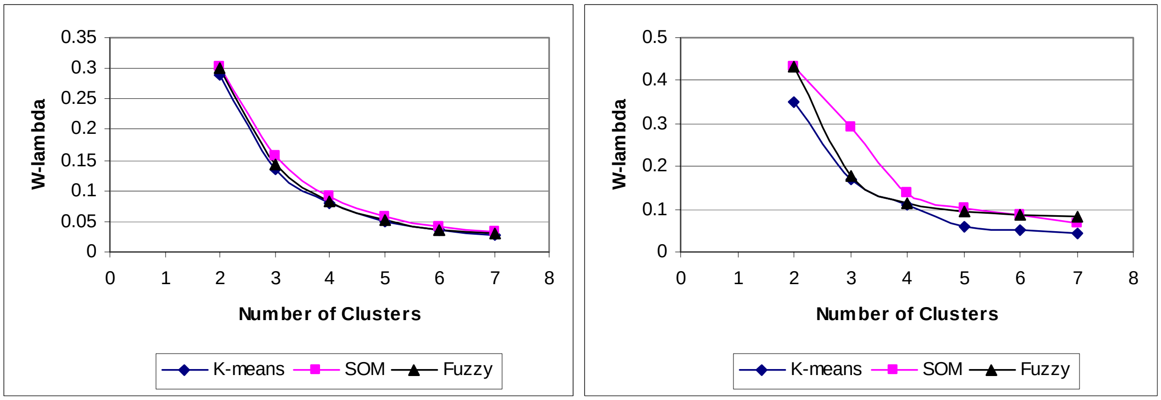
T = total variance

Average RD based on cycle length (CBA) and fixed time (FTA) intervals were used for clustering. An interval of 60 seconds was used for FTA analysis. Figure 6 and 7 show the results of clustering for CBA and FTA approaches, respectively.



(a) Through vehicles (b) Right vehicles

Figure 6 Clustering results based on cycle length based aggregation (CBA)



(a) Through vehicles (b) Right vehicles

Figure 7 Clustering results based on fixed time aggregation (FTA)

As we can identify in the clustering results, significant marginal improvement due to a decreasing value of Wilk's lambda is not observed after 5 groups, which means the most appropriate number of clusters or LOS categories for the data used is 5. In addition, the overall values of Wilk's lambda from K-means clustering are lower than for the other methods, so the threshold values were determined by K-means clustering. Based on these results, real-time LOS criteria for this signalized intersection can be stated in terms of RD averaged over the cycle length or a fixed 60 seconds interval as shown in Table 3. Other longer time intervals could also be used, but if too long, would detract from the "real-time" capabilities of the approach.

Table 3 Real-time signalized intersection LOS criteria

LOS Category		LOS criteria (average RD, sec)			
		Through vehicles		Right vehicles	
		CBA	FTA(1min)	CBA	FTA(1min)
I	(Excellent)	≤ 14	≤ 13	≤ 12	≤ 13
II	(Very Good)	> 14 and ≤ 27	> 13 and ≤ 27	> 12 and ≤20	> 13 and ≤ 21
III	(Good)	> 27 and ≤ 41	> 27 and ≤ 45	> 20 and ≤30	> 21 and ≤ 34
IV	(Fair)	> 41 and ≤ 60	> 45 and ≤ 66	> 30 and ≤ 43	> 34 and ≤ 51
V	(Poor)	> 60	> 66	> 43	> 51

For comparative purposes, the six HCM LOS categories based on control delay are presented in Table 4. Because the measurement of control delay in real-time is not trivial task, we believe that RD may be more effectively utilized for LOS analysis.

Table 4 HCM LOS Criteria

Level Of Service	Control Delay per Vehicle (sec)
A	≤ 10
B	>10 and ≤ 20
C	>20 and ≤ 35
D	>35 and ≤ 55
E	>55 and ≤ 80
F	> 80

An analysis of the errors between average RD and actual intersection delay obtained by video ground-truthing for both CBA and FTA aggregation periods yielded the results in Table 5. A mean absolute percentage error (MAPE) was used to compute the errors.

$$MAPE = \frac{\sum_{i=1}^{N}\left[\left|\frac{ARD_i - AAD_i}{AAD_i}\right| \times 100\right]}{N}$$

$where,$

ARD_i = Average Reidentification Delay at time step i

AAD_i = Average Actual Delay at time step i

N = Total number of time step

Table 5 Reidentification Delay (RD) errors for different aggregation intervals

Aggregation period	Through vehicles	Right vehicles
Cycle (CBA)	25.0 %	27.0 %
1 min (FTA)	32.3 %	26.3 %

The results in Table 5 are dependent on the matching rates achieved by the vehicle reidentification algorithm; as those rates improve so will the errors above. However, even with the initial reidentification performance on which Table 5 and the LOS criteria in Table 3 are based, the results are believed to be very encouraging.

The authors believe that cycle length may be the shortest appropriate interval to use for data aggregation and LOS purposes, which suggests use of the CBA LOS criteria. In addition to an ability to derive real-time LOS criteria, an advantage of the underlying vehicle reidentification approach is that it permits separate LOS criteria to be developed for through and turning vehicles.

To illustrate the application of the results in Table 3, consider the actual data and calculated cycle lengths from Figure 5. In an on-line situation, the average RD would be calculated at the end of each cycle by the system, and then assigned an appropriate LOS from Table 3. In such applications, data aggregation issues could emerge since the stability of delay might be highly variable due to the interruption of signal control. One could consider the following characteristics regarding aggregation interval: first of all, dynamic behavior of traffic conditions should be captured by a short aggregation interval. On the other hand, we should be able to provide reliable and stable information, which means, for example, if real-time LOS fluctuates in a short time period, some users might not perceive it as being useful. As one possible solution, a rolling average RD can be used to determine LOS. An aggregation interval that shows a stable change of LOS, would be desirable. Various aggregation steps from 1-cycle to 5-cycle case were analyzed. As a result, a 3-cycle rolling average was identified as a reasonable aggregation that satisfied above argument. This is illustrated in Table 6.

Table 6 Real-time LOS analysis

Cycle	Clock Time	Cycle length (sec)	Through Movement				Right-turn Movement			
			1-cycle Average		3-cycle Rolling Average		1-cycle Average		3-cycle Rolling Average	
			RD (sec)	LOS	RD (sec)	LOS	RD (sec)	LOS	RD (sec)	LOS
1	17:00:00 - 17:01:23	83	32.0	III	33.9	III	23.3	III	21.7	III
2	17:01:24 - 17:03:06	102	25.5	II	32.5	III	19.0	II	22.4	III
3	17:03:07 - 17:04:18	71	11.6	I	23.0	III	6.5	I	16.3	II
4	17:04:19 - 17:05:41	82	23.4	II	20.2	II	20.0	II	15.2	II
5	17:05:42 - 17:07:30	108	45.2	IV	26.7	II	28.1	III	18.2	II
6	17:07:31 - 17:08:34	63	23.5	II	30.7	III	13.6	II	20.6	II

The LOS determined in Table 6 for each cycle could be communicated in real-time to the operating agency's traffic management center, either for direct operator evaluation, or as input to other software applications, such as congestion monitoring.

CONCLUSIONS

The U.S. Highway Capacity Manual (HCM) presents a procedure for estimating control delay, which is used to determine Level Of Service and to evaluate intersection performance. The HCM is used extensively by traffic engineers. However, it is intended as an off-line decision support tool for planning and design. To meet the user requirements of Advanced Traffic Management Systems, new LOS criteria are required for real-time intersection analysis. The objective of this research was to demonstrate a technique for development of such LOS criteria. The study used a new measure of effectiveness, called Re-identification Delay (RD) derived from analysis of vehicle inductive signatures and reidentification of vehicles traveling through a major signalized intersection in the City of Irvine, California.

This paper tackled two main issues regarding real-time LOS criteria. The first was how to determine the threshold values partitioning the LOS categories. To provide reliable real-time traffic information, the threshold values should be decided so that RDs within the same LOS category should represent similar traffic conditions as much as possible. On the other hand, RDs in different LOS categories should also represent dissimilar traffic conditions. The second issue concerned the aggregation interval to use for RD in deriving LOS categories. An investigation of both fixed and cycle-based aggregation intervals was conducted. Several clustering techniques were then employed to derive LOS categories, including K-means, Fuzzy, and Self-Organizing Map (SOM) approaches. The resulting real-time LOS criteria were presented. The procedures used in this study are readily transferable to other signalized intersections for the derivation of real-time LOS.

In this study, upstream and downstream detectors were used that are not typical detector configuration found in current practice. Our on-going research is undertaking studies of detector configurations that are able to satisfy the needs of both signal control and vehicle reidentification.

It is believed that the initial techniques for development of real-time LOS criteria developed in this study have provided very encouraging results and offer a valuable tool to operating agencies in support of congestion monitoring, real-time control, and system evaluation. Furthermore, the information could be used for real-time traveler information.

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