Real-Time Freeway Level of Service Based on Anonymous Vehicle Re-Identification

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ABSTRACT
The performance of freeways is evaluated based on the levels of service (LOS) described by The Highway Capacity Manual (HCM). Apart from being essentially an offline decision support tool for planning and design, it is also based on point measurements from loop detectors, which may not provide an accurate assessment of freeway section performance. In order to meet user requirements of advanced traffic management and information systems (ATMIS), new LOS criteria based on section measures are required for real-time freeway analysis. The main aim 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 travel time (RTT), derived from analysis of vehicle inductive signatures and re-identification of vehicles traveling through a major section of freeway in the city of Irvine, California. Two real-time LOS issues were addressed in this paper. 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 such that section travel times within the same LOS category represent similar traffic conditions as much as possible. Also, section travel times in different LOS categories should represent different traffic conditions. The second issue concerned the aggregation interval to use for deriving LOS categories. Two clustering techniques were then employed to derive LOS categories, namely k-means and fuzzy approaches. The resulting real-time LOS criteria are presented in this paper. The procedures used in this study are readily transferable to other similarly equipped freeway sections for the derivation of real-time LOS.

INTRODUCTION
The performance of freeways is evaluated based on the levels of service (LOS) described by The Highway Capacity Manual (HCM). It uses quantitative measures that characterize operational conditions within a traffic stream. The descriptions of individual levels of service characterize these conditions in terms of such factors as speed and travel time, freedom to maneuver, traffic interruptions, and comfort and convenience (J). Apart from being essentially an offline decision support tool for planning and design, it is also based on point measurements from loop detectors, which may not provide an accurate assessment of freeway section performance. In order to meet user requirements of advanced traffic management and information systems (ATMIS), new LOS criteria based on section measures are required for real-time freeway analysis. The main aim 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 travel time (RTT), derived from analysis of vehicle inductive signatures and re-identification of vehicles traveling through a major section of freeway in the city of Irvine, California. RTT is defined as the actual time required to traverse contiguous vehicle re-identification stations on a section of freeway. The availability of real-time LOS is significantly
important 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 freeways are stated in terms of the average vehicle density from point measures. With the capability to obtain vehicle travel times for sections of freeways from a re-identification system, there is a possibility of obtaining new LOS criteria that can be used for real-time freeway analysis on continuous sections. Two viewpoints can be considered for the purpose of real-time freeway analysis. First, operating agencies need to obtain real-time conditions in order to control and manage traffic systems. Second, drivers or users of traffic systems require updated and reliable traffic information to decide their route choice in real time.

Several studies have been carried out in relation to deriving LOS criteria. Cameron (2) and Baugnauten (7) proposed extending the LOS criteria from A to J and A to I respectively from the existing HCM A through F criteria. Their concern was derived from longer delay due to increasing urban traffic congestion. Hence, they proposed criteria representing traffic conditions beyond LOS F by adding extra categories somewhat arbitrarily. Pecteux et al. (4) presented preliminary analyses about how users perceive LOS and how many levels are perceived. The results indicated that two or three LOS were generally perceived. More recently, Oh and Ritchie (5) presented a new method of obtaining real-time LOS for signalized intersections from vehicle inductive signatures. However, it appears that no study has yet been attempted to develop real-time LOS criteria for freeway sections.

This study is an extension of the work of Oh and Ritchie (5) to freeway sections, and 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 determined such that RTTs within the same category represent similar traffic conditions as much as possible. Conversely, RTTs in different LOS categories should also represent dissimilar traffic conditions. The second issue involves the aggregation interval to use for RTT in deriving LOS categories. A practical real-time information system should have an aggregation interval small enough to capture the dynamics of traffic flow. However, it also needs to be sufficiently large such that the system is relatively stable, as an information system that has a high fluctuation would not be useful for traffic users. Two clustering techniques were employed here to derive LOS categories, namely k-means and fuzzy approaches.

The new LOS criteria presented here can be used to provide both operating agencies and drivers with traveler information as well as evaluate real-time freeway section performance.

**FREeway VEHICLE REIDENTIFICATION**

A real-time traffic surveillance system based on vehicle inductive signatures and vehicle re-identification (REID) technique has been implemented on the Northbound Interstate
405 (I-405) freeway in the city of Irvine, California. The 0.7 mile freeway section consists of two contiguous detection stations at Laguna Canyon and Sand Canyon and has been equipped with double (square) inductive loops in each lane. Vehicle signature data are extracted in real-time by high-speed scanning loop detector cards and stored in dedicated computers in the field. Data are then transmitted from the field by a dedicated wireless Ethernet connection.

A freeway vehicle re-identification system based on the concept of the lexicographic optimization method developed by Sun et al. (6) has been implemented on this freeway section. It has also been reported by Sun et al. that the average percent error for travel times obtained by the vehicle re-identification under congested traffic conditions is 3.25%, which is quite accurate.

The vehicle re-identification is running on site locally, and generating invaluable section-based traffic parameters including travel times and individual vehicle trajectories by matching vehicle signatures between upstream and downstream sites. The outputs of the system are sent to the data center at University of California, Irvine (UCI) over the internet and received by the data collection server, and then stored in the database server. The web server queries data from database, and performs data processing to provide more useful traffic information such as data aggregation and the generation of data tables and data graphs.

The vehicle re-identification system has been operating in real-time. The results include not only point traffic parameters such as volume and speed for each detection station but also section traffic parameters including section volume, section speed, and travel times.

**Vehicle Re-identification Algorithm**

A variety of useful information is extracted from the inductive vehicle signatures representing the unique characteristics of individual vehicles. In addition, other information including arrival time, duration, lane, and speed for individual vehicles can also be obtained. Extensive research using inductive vehicle signature has been performed, and its effectiveness for various transportation applications has been demonstrated in previous studies (5, 7 & 8). Figure 1 shows some characteristics of typical signatures obtained from the freeway high-speed loop detectors. The vertical axis in each case is proportional to the change in inductance, and the horizontal axis represents time (in milliseconds). Figure 2 shows the overall vehicle re-identification algorithm. Further details are discussed by Ritchie et al. (9).
FIGURE 1  Typical signature obtained from freeway high-speed loop detectors.

FIGURE 2  Freeway vehicle re-identification flowchart.
Travel Time Analysis

A preliminary study was made to determine the goodness-of-fit for RTT distributions obtained from REID with actual traffic data. Twenty minutes of REID and video ground-truthed data were obtained on July 23 2002, between 15:00 and 15:20 on the N I-405 between Laguna Canyon and Sand Canyon. The data were aggregated into 15-second intervals for goodness-of-fit tests. Results showed that the REID data provided a good fit for actual traffic data at a 5% level of significance based on both the Chi-square and Kolmogorov-Smirnov goodness-of-fit tests. In addition, RTT distributions based on median travel times were more statistically significant than mean travel times. The results demonstrated that the REID system is capable of producing accurate estimates of travel time information on freeways.

METHODOLOGY FOR DETERMINING LOS CRITERIA

The RTT threshold values used to partition LOS designations should effectively reflect real-time traffic conditions in each category. The objective of the partitioning is to obtain homogeneity of RTT within the same categories (i.e., data belonging to the same category should be as similar as possible) and heterogeneity of RTT between categories (i.e., data belonging to different categories should be as different as possible). A solution can be obtained to satisfy the abovementioned constraints through the formulation of two maximization problems: first, to maximize the dissimilarity between categories and second, to maximize similarity within categories. Consistent with this maximization, clustering algorithms were applied to determine the optimal number of categories in a given data set. Unlike classification, cluster analysis makes no prior assumptions concerning the number of groups. Instead, it seeks to partition a given set of data or objects into clusters. \(k\)-Means clustering and fuzzy clustering were investigated in this study.

For clustering analysis, the RTT taken by individual vehicles passing between adjacent upstream and downstream detector stations is the output of the surveillance system used. Nine days of field data representing a range of traffic conditions at the study freeway section were selected by field investigation of daily traffic patterns. The dates, time periods as well as the number of vehicles recorded are shown in Table 1. A total of 185,862 vehicles were re-identified in these sampling periods. Effects of seasonal variations were considered during the analysis, but if these effects were infrequent, they would not be representative of normal traffic behavior and therefore were not applicable. It was desired to use data under normal operating conditions, as was the case for the data collection periods in this study. The RTTs of individual vehicles were aggregated into short time intervals, so that the representative RTT of each interval could serve as the basis for the cluster analysis. Considering that median travel times provided a better fit than mean in the previous travel time analysis, and that some previous work show that the median travel times provide better estimates than means (10), the median RTT was used to represent each interval.
Table 3  Collected Data for Clustering Analysis

<table>
<thead>
<tr>
<th>Data</th>
<th>Time Period</th>
<th>Number of Vehicles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sep 7, 2002</td>
<td>06:25 ~ 13:33</td>
<td>37,182</td>
</tr>
<tr>
<td>Sep 27, 2002</td>
<td>06:25 ~ 13:32</td>
<td>19,007</td>
</tr>
<tr>
<td>Sep 29, 2002</td>
<td>06:20 ~ 13:33</td>
<td>14,602</td>
</tr>
<tr>
<td>Oct 7, 2002</td>
<td>05:25 ~ 12:37</td>
<td>13,815</td>
</tr>
<tr>
<td>Oct 9, 2002</td>
<td>05:25 ~ 12:40</td>
<td>16,731</td>
</tr>
<tr>
<td>Oct 11, 2002</td>
<td>05:25 ~ 00:37</td>
<td>50,728</td>
</tr>
<tr>
<td>Oct 16, 2002</td>
<td>05:20 ~ 12:41</td>
<td>14,880</td>
</tr>
<tr>
<td>Oct 23, 2002</td>
<td>05:20 ~ 12:39</td>
<td>6,276</td>
</tr>
<tr>
<td>Oct 25, 2002</td>
<td>05:25 ~ 12:33</td>
<td>12,691</td>
</tr>
</tbody>
</table>

$k$-Means Clustering

$k$-means clustering is a well-known partitioning methods (11). The algorithm computes $k$ representative objects called medoids, which together determine a cluster. The number $k$ of clusters is an argument of the function. Each object is then assigned to the cluster corresponding to the nearest medoid. Hence, object $i$ is placed into cluster $v_l$ when it is closer to medoid $m_{w_i}$ than any other medoid $m_v$:

$$d(i, m_{w_i}) \leq d(i, m_v) \quad \text{for all } w = 1, \ldots$$

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

Objective function $= \sum_{m}^{k} d(i, m_{w_i})$

Fuzzy Clustering

In fuzzy clustering, each observation is given fractional membership to multiple clusters. For each object $i$ and each cluster $v$, the membership $u_{iv}$ indicates the affinity of object $i$ to cluster $v$. Memberships have to satisfy the following conditions (12):

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

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

The memberships are defined through minimization of (11)
Objective function = \sum_{i=1}^{n} \sum_{j=1}^{n} u_{i,j}^2 d(i,j) \\
\sum_{i=1}^{n} \sum_{j=1}^{n} u_{i,j}^2 \frac{1}{2n \sum_{i=1}^{n} n_{r,i}^2}

In the preceding expression, the dissimilarities \(d(i,j)\) are known and the membership \(u_{i,r}\) is unknown. The minimization is numerically computed by an iterative algorithm with the above constraints. The result of fuzzy clustering can be shown as crisp clusters by assigning each object \(i\) to the cluster \(r\) in which it has the highest membership \(u_{i,r}\).

Clustering Results

Wilk’s Lambda (\(\Lambda\)) was used to compare the results of k-Means and fuzzy clustering techniques. It is defined as the ratio of within group variance to total variance. Hence, a lower Wilk’s lambda represents better clustering (13).

\[ \Lambda = \frac{|W|}{|T|} = \frac{|W|}{|B + W|} . \]

where
\[ W = \text{pooled within-group variance}, \]
\[ B = \text{between-group variance}, \]
\[ T = \text{total variance} \]

Medians of RTT, using seven different rolling median aggregation time intervals (15, 30, 60, 120, 180, 240 and 300 sec) were used in the clustering analysis. For all aggregation intervals, the median RTT was updated every 15 seconds. Cluster sizes from two to ten were analyzed for both k-Means and fuzzy clustering methods. Figures 3a and 3b show the results of clustering using aggregation time intervals of 15 and 240 seconds respectively.

From the seven aggregated time intervals and nine different cluster sizes used for each interval, 63 pairs of results for k-Means and fuzzy clustering were obtained with the Wilk’s Lambda parameter used as the measure of effectiveness. Using the Sign Test for paired samples, it was found that k-Means provided better clustering results at a 5% level of significance. This indicated that k-Means was a better clustering technique in this application.
FIGURE 3  Clustering results based on (a) 15 sec aggregation interval and (b) 240 sec aggregation interval in 15 sec time steps

LOS Stability

In an online situation, the median RTT would be calculated at the end of each time step, and then assigned an appropriate LOS according to the nearest cluster center. Two main concerns arise. Firstly, the system should have the ability to capture the dynamic behavior of traffic conditions. Yet, it also needs to provide reliable and stable information. This means that if real-time LOS fluctuates significantly in a short time period, users would not perceive it as being useful and reliable. Hence, an aggregation interval that shows a stable change of LOS would be desirable (5).

By visual comparison of Figures 4a and 4b, a 240 sec aggregation interval provides a significantly more stable change in LOS over a 60 sec aggregation interval. The stability of different aggregation time intervals was measured by the percentage of abrupt LOS jumps in adjacent time steps over the total number of time steps recorded in the day. Data from October 16 2002 were used in this analysis.

FIGURE 4  Level of Service during time of day for 6 clusters: (a) 60 sec aggregation interval and (b) 240 sec aggregation interval

Two measures of stability were used in this analysis: percentage of two or more LOS jumps and percentage of three or more LOS jumps, the latter indicating the proportion of more abrupt changes in LOS between adjacent time steps. The analysis was repeated from two clusters to ten clusters for all time intervals. From Figures 5a and 5b, the
optimum aggregation interval indicated by the lowest percentage of two or more and three or more LOS jumps were obtained at 240 sec aggregation interval. Aggregation at 300 sec did not provide significant improvements for percentage of two or more LOS jumps and resulted in a higher percentage of three or more LOS jumps when compared with the 240 sec aggregation interval.

![Graphs showing percentage of LOS jumps for different aggregation intervals with 6 and 8 clusters.](image)

(a) (b)

**FIGURE 5** Percentage of LOS Jumps for k-Means: (a) 6 clusters and (b) 8 clusters

**Optimal Cluster Size**

Several factors influence the ‘optimal’ cluster size to be chosen. Increasing the number of clusters would generally decrease the Wilk’s Lambda parameter, which indicates a smaller variance within clusters compared with the overall variance. Although this is desired, increasing the number of clusters also increases the proportion of LOS jumps between adjacent time steps, decreasing stability in the system. To obtain the best cluster size two measures of effectiveness were used. The first measure is the marginal percentage improvement in Wilk’s Lambda parameter as the cluster sizes increase. The second is the marginal percentage increase in LOS jumps. The selection criteria for a cluster requires a large marginal percentage improvement in Wilk’s Lambda parameter and a small marginal percentage increase in LOS jumps.

From Figure 6, k-Means with 6 clusters provided the best results. Although the marginal improvement in Wilk’s Lambda is not large, it is overshadowed by the low marginal percentage increase in LOS jumps. Results with 8 and 9 clusters are also reasonable based on the criteria given above.
FIGURE 6  Marginal change of Wilk's Lambda and LOS Jumps for different k-Means cluster sizes

The HCM presently uses six levels of service for freeways. In addition, Pecheux et al. also presented preliminary analyses about how users perceive LOS and how many LOS categories are perceived (4). The results indicated that two to three LOS categories were generally perceived. Hence there would be little value in considering cluster sizes larger than 6, since it would be difficult for users to perceive the difference between adjacent LOS. Therefore, six clusters would be ideal in this application.

From these results, real-time LOS criteria for this freeway section based on six clusters were defined in terms of median section travel time over a fixed 240 sec interval, as shown in Table 2. The LOS were categorized from I to VI, ranging from excellent to very poor.

<table>
<thead>
<tr>
<th>LOS Category</th>
<th>LOS Criteria (Median Travel Time, sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I (Excellent)</td>
<td>$\leq 29.4$</td>
</tr>
<tr>
<td>II (Very Good)</td>
<td>$29.4 \leq$ and $\leq 33.4$</td>
</tr>
<tr>
<td>III (Good)</td>
<td>$33.4 \leq$ and $\leq 38.5$</td>
</tr>
<tr>
<td>IV (Fair)</td>
<td>$38.5 \leq$ and $\leq 47.1$</td>
</tr>
<tr>
<td>V (Poor)</td>
<td>$47.1 \leq$ and $\leq 58.5$</td>
</tr>
<tr>
<td>VI (Very Poor)</td>
<td>$&gt; 58.5$</td>
</tr>
</tbody>
</table>

Figures 6 and 7 show the LOS criteria applied to traffic data obtained from October 16 2002. About 80% of the data falls within LOS II or better and 90% falls within LOS IV or better, as shown in Figure 6.
FIGURE 6 Cumulative Travel Time Distribution for REID data obtained from October 16 2002.

FIGURE 7 Travel Time Density Distribution for REID data obtained from October 16 2002.

CONCLUSION
The HCM presents a procedure for determining LOS to evaluate freeway performance. The HCM is used extensively by traffic engineers. However, it is intended as an offline decision support tool for planning and design. Moreover, the HCM criteria are based on point measures from loop detector stations. Hence, new LOS criteria are needed for real-time analysis of freeway sections to meet user requirements of advanced traffic management and information systems. This research has sought to demonstrate a technique for the development of such LOS criteria. The study used median section travel time as a new measure of effectiveness, derived from analysis of vehicle inductive signatures and re-identification of vehicles traveling through a major freeway section in Irvine, California.
Two main issues regarding real-time LOS criteria were addressed. 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 such that median section travel times within the same LOS category represent similar traffic conditions as much as possible. Also, median section travel times in different LOS categories should represent dissimilar traffic conditions. The second issue concerned the aggregation interval to use for deriving LOS categories. Two clustering techniques were then employed to derive LOS categories, namely k-means and fuzzy approaches. The resulting real-time LOS criteria were presented in this paper. The procedures used in this study are readily transferable to other similarly equipped freeway sections for the derivation of real-time LOS.

The proposed techniques for development of real-time LOS criteria developed in this study have provided encouraging results and are potentially valuable to operating agencies in support of congestion monitoring, real-time control, and system evaluation. In addition, the information could be used for real-time traveler information.

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REFERENCES


