Real-Time Detection of Hazardous Traffic Conditions on Freeways

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Real-time detection of hazardous traffic conditions on freeways

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ABSTRACT

This study develops a new methodology for evaluating one aspect of freeway safety performance in real time. In contrast to the prevalent performance measures based on mobility, a new index is derived to represent freeway safety levels obtained from a surrogate measure for rear-end collisions. The application of the proposed study is demonstrated with actual data. Advanced inductive loop detector technology is utilized to monitor individual vehicle information on the freeway that will be used for computing the stopping distances in car-following situations. In addition, real-time safety-based level of service criteria are developed in order to provide more effective information to users. It is believed that the proposed methodology for evaluating real-time safety performance on freeways could be a valuable tool to operating agencies in support of countermeasure development to prevent accident occurrence. Furthermore, the information could be used as a basis of a driver warning system leading to safer and careful driving.
INTRODUCTION

A first step for tackling complex transportation problems is to identify and evaluate the current status of dynamic traffic conditions. How to effectively measure traffic performance is a crucial element to devise viable solutions to traffic problems. Measuring traffic performance can be conducted from two different perspectives such as ’mobility’ and ’safety’. A variety of studies have focused on assessing transportation systems based on mobility by utilizing travel time, speed, and other fundamental traffic parameters. Such mobility-based evaluations support advanced traffic control strategies including route guidance and ramp control etc. On the other hand, less effort has been devoted to develop methodologies for safety-based performance evaluation in real time, although research subjects on safety are often regarded as more important ones because of direct impacts on human lives. The limitations associated with the use of actual accident data, such as unreliability of accident occurrence time and location, are the main obstacle to safety-based performance evaluation. Moreover, to obtain a large sample of accident data that is sufficient to provide statistical significance in developing models is not a trivial task.

To assist in the establishment of safety policies, which is the main research purpose of much of the literature about traffic safety, the abovementioned limitations might not be crucial. However, those limitations can not be disregarded in order to evaluate real-time traffic safety performance measures because accurate and reliable accident data are required to be analyzed with real-time traffic conditions. The limitations lead to keen interest in developing ‘safety surrogate measures’ to represent the level of safety with quantified indices. One promising alternate is the traffic conflict technique.

A conflict can be defined as an observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged (1). Various studies dealing with traffic conflict techniques can be readily found in the literature. However, so far we are not aware of any study using such techniques in a real time environment that can be implemented for evaluating real-time traffic safety performance measures.

In the past, disaggregated real-time traffic data were not readily obtainable, which was one of the reasons that existing studies just used aggregated traffic data. However, with the advent of intelligent transportation systems (ITS), traffic agencies have implemented instrumented traffic monitoring systems, for example advanced inductive loop detectors that are capable of providing real-time traffic data in a very detailed level. Therefore, research needs to measure traffic safety performance, which can be used for establishing countermeasures to prevent traffic accidents, by utilizing real-time traffic data. From this perspective, the traffic conflict technique needs to be upgraded by the use of recently developed technologies, and such needs initiated this study.

Two traffic conflicts can be observed on freeways. One is a lane change conflict occurring when a vehicle attempts to change lanes. The other one is rear-end conflict resulting potentially in rear-end crash. This study focuses on the derivation of a new
safety index by incorporating both an advanced inductive loop detector technology capable of producing individual vehicle information, and rear-end conflicts, which can be used in real-time traffic situations. In addition, a clustering technique is further applied to categorize the proposed safety index, so that it can be more readily used as not only for real-time safety level of service but also safety information.

A Fuzzy c-means (FCM) algorithm is employed to cluster traffic conditions. 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. Therefore, the degree of membership can be used for quantifying reliability for uncertainty arising in evaluating real-time safety performance measures.

The outcomes of this study that measure and quantify real-time traffic safety performance could be an invaluable tool for traffic operators in evaluating traffic systems in terms of safety. In addition, the approach could support the development of effective countermeasures to prevent rear-end traffic accidents on freeways.

This paper consists of four sections, including the introduction. The proposed methodology for evaluating freeway safety is presented in Section 2. Section 3 describes the data used in this study, and presents both results and their application. Finally, the conclusions are provided.

PROPOSED METHODOLOGY

To develop a methodology for evaluating real-time traffic safety performance on freeways, this study uses individual vehicle information and a traffic conflict technique. Advanced inductive loop detector technology that produces unique inductive vehicle signatures for each vehicle passing over a loop detector station is employed to monitor detailed individual vehicle information. Use of inductive vehicle signatures also allows us to classify vehicle types in real time based on the analysis of vehicle features extracted from the inductive vehicle signatures. This vehicle classification information is highly valuable for identifying unsafe car following situations since the performance of large vehicles and their effects on neighboring vehicles are obviously different from relatively small vehicles. Large vehicles involved in accidents usually show higher severity of injury due to the operating characteristics of large vehicles, such as long vehicle length, heavy weight, and longer stopping distance. In addition, large vehicles limit the capability of following vehicles to identify traffic conditions ahead, which could increase the possibility of rear-end collisions.

A new safety index based on rear-end conflicts derived from advanced inductive loop detector technology was utilized to evaluate traffic safety on a freeway in real time. The basis of the proposed safety index is obtained from the computation of the safety distance defined by the difference between a leading and following vehicles' safe stopping distances. The safe stopping distance of a leading vehicle should be always greater than
that of a following vehicle to prevent an accident when the driver of the following vehicle identifies the leading vehicle is stopping and needs to apply braking.

In order to use the proposed safety index more effectively, a clustering technique was further applied to categorize the index. It can result in various levels of safety, which can be used for evaluating traffic safety. Figure 1 shows the framework for evaluating safety of freeways based on the proposed methodology. More detailed descriptions for each element are presented in the following subsections.

**Figure 1 Research framework**

### Monitoring individual vehicle information from inductive loop detectors

The proposed methodology utilizes inductive loop detectors (ILDs) that are the dominant traffic surveillance infrastructure in practice currently. Traditional loop detectors are able to provide fundamental traffic parameters such as volume, occupancy, and speed by determining if inductance changes are significant enough to indicate a vehicle passing over the loop. The output signal is usually binary, such as either 0 for non-presence or 1 for presence. Then, aggregated output is obtained over a pre-determined aggregation interval, for example 20 or 30 seconds. However, we are able to obtain disaggregated information for individual vehicles by using advanced high speed scanning loop detector
cards that capture more detailed inductance changes over the loops. The result is an inductive vehicle signature.

A variety of useful information can be extracted from the inductive vehicle signatures, which represent the unique characteristics of individual vehicles. In addition, other information including arrival time, duration, lane, and speed for individual vehicles can be collected. The disaggregated information for each vehicle was utilized to classify vehicle types, and then derive the safety index for evaluating real-time safety performance in this study. Extensive research using inductive vehicle signatures has been performed, and its effectiveness for various transportation applications has been demonstrated in previous studies (2-4). Figure 2 shows examples of inductive vehicle signatures.

![Image of vehicle signatures](image)

(a) Truck

(b) Passenger Car

Figure 2 Inductive vehicle signatures for different vehicle types

Maximum magnitude, electronic vehicle length, shape parameter (SP), degree of symmetry (DOS), and number of samples of high magnitudes (NHM) are examples of vehicle features derived from inductive vehicle signatures. Figure 3 shows the scheme for vehicle signature processing, and detailed descriptions for vehicle features are presented in Table 1.
Table 1 Vehicle feature examples

<table>
<thead>
<tr>
<th>Feature Vector</th>
<th>Feature Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Magnitude</td>
<td>Maximum absolute magnitude value (a)</td>
</tr>
<tr>
<td>Electronic Vehicle Length</td>
<td>(d)</td>
</tr>
<tr>
<td>Shape Parameter (SP)</td>
<td>(b)/(b+c))</td>
</tr>
<tr>
<td>Degree of Symmetry (DOS)</td>
<td>Sum of the distances from median (e), to each point that is above “0.5” y value</td>
</tr>
<tr>
<td>Number of High Magnitude (NHM)</td>
<td>Number of sample above “0.5” y value after x,y normalization</td>
</tr>
</tbody>
</table>

Vehicle classification

The proposed safety index that will be introduced in the next section is based on safety distances of the lead and following vehicles in each car-following situation. Vehicle performance is one of the major factors in computing safety distance. Therefore, identifying vehicle types enables us to apply various vehicle deceleration performances, resulting in more accurate safety distances. The vehicle classification capability also supports the evaluation of real-time traffic safety in terms of indicating accident severity in unsafe car-following situations, because large vehicle-involved accidents show more severe damage, as found in many previous studies. In addition, vehicle classification information can be used not only for traffic flow modeling and simulation but also for highway maintenance.

Vehicle features obtained by processing raw signatures as shown in Figure 3 can be utilized for identifying vehicle classes since the vehicle signature is a function of the vehicle type. Vehicle classification in this study consists of two parts: feature extraction from the inductive vehicle signatures and development of a heuristic discriminant.
algorithm. The heuristic discriminant algorithm utilizes vehicle feature vectors obtained from inductive vehicle signatures as inputs.

**Derivation of a new safety index**

Rear-end collisions have been identified in the literature as one of the main crash types on freeways. For example, Golob et al. (5) have analyzed freeway accident data in Southern California and found rear-end collisions are over 30% of total accidents. From this perspective, identifying rear-end conflicts potentially leading to rear-end collisions is very useful for evaluating safety. Since a rear-end collision is primarily caused by the fact that the safety distance between the leading vehicle and the following vehicle is not maintained, a method to obtain safety distance from a freeway real-time monitoring system is of keen interest for establishing a safety performance measure.

One of the nicest features of the monitoring system in this study is to compute vehicles’ safe stopping distances. In order to prevent rear-end collision, a longer safe stopping distance of a lead vehicle than that of a following vehicle is required. Various vehicle performances represented by deceleration rates can be applied based on vehicle types determined by the preceding vehicle classification procedure. The stopping distance index is derived as follows.

\[
d_{L} > d_{F} \Rightarrow V_{L} \times h + \frac{V_{L}^{2}}{2a_{L}^{F}} > V_{F} \times t_{b} + \frac{V_{F}^{2}}{2a_{F}^{F}}
\]

\[
\therefore SDI = \begin{cases} 
0 & \text{(safe) if } V_{L} \times h - V_{F} \times t_{b} + \left( \frac{V_{L}^{2}}{2a_{L}^{F}} - \frac{V_{F}^{2}}{2a_{F}^{F}} \right) > 0 \\
1 & \text{(unsafe), otherwise}
\end{cases}
\]

where

- **SDI** : stopping distance index for each car-following event
- **d_{L}** : safe stopping distance of leading vehicle
- **d_{F}** : safe stopping distance of following vehicle
- **V_{L}** : speed of leading vehicle
- **V_{F}** : speed of following vehicle
- **t_{b}** : brake reaction time
- **h** : time headway
- \(a_{L}^{F}\) : deceleration rate of leading vehicle
- \(a_{F}^{F}\) : deceleration rate of following vehicle

As a result, the number of stopping distance indices (SDIs) less than zero, observed over a given time period, is used to derive a real-time safety index (RSI). In general, the index representing the safety level is described in the form of rates, which is a function of accident or conflict counts and an exposure measure. It should be noted that the exposure
measure needs to be employed to establish the safety index as the base because providing total accident or conflict counts would be misleading.

This study employs the maximum possible number of car-following situations over a certain time interval as an exposure. The proposed RSI, which is a surrogate measure for rear-end collision, is defined as the ratio of the number of unsafe car-following events showing a safety distance index less than zero to the maximum possible car-following events on freeway detector stations. An unsafe car-following event is derived from the computation of safe stopping distance presented above, and a maximum car-following event can be derived by the minimum headway that results in freeway capacity. The proposed RSI is described as follows.

\[
RSI = \frac{\text{number of rear-end conflicts}}{\text{Exposure}} = \sum \frac{SDI_i}{N_{\text{Car}}^{\text{Max}} \times \left(\frac{5600}{T}\right) \times N_i}
\]

where,
\[
RSI: \text{real-time safety index}
\]
\[
N_{\text{Car}}^{\text{Max}}: \text{maximum number of car-following events per hour (derived from freeway capacity)}
\]
\[
N_i: \text{number of freeway lanes}
\]
\[
T: \text{analysis period (sec)}
\]

Development of real-time safety-based level of service (S-LOS)

The proposed RSI is categorized by the threshold values to be used by users including operating agencies and drivers. The basic background for categorization is that RSIs within the same category represent similar traffic conditions as much as possible in terms of traffic safety. On the other hand, RSIs in different categories should also represent dissimilar traffic conditions in terms of traffic safety. A solution that can satisfy the above two aspects 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 a clustering algorithm to determine the “optimal” number of categories in a given data set. A Fuzzy c-means (FCM) algorithm was employed to cluster traffic conditions. 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. Therefore, the degree of membership can be used for quantifying reliability for uncertainty arising in evaluating real-time safety performance measures.

FCM was originally proposed by Bezdek (6) by using fuzzy factors. Fuzzy clustering problems can be formulated as the following minimization problem.

9
\[
\min J_u(U, V) = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^m d_{ij}^2,
\]
\[
\begin{cases}
  d_{ij} = |x_j - v_i| \\
  \sum_{i=1}^{n} u_{ij} = 1, \quad 1 \leq j \leq n \\
  u_{ij} \geq 0, \quad 1 \leq i \leq n, \quad 1 \leq j \leq n \\
  \sum_{j=1}^{n} u_{ij} > 0, \quad 1 \leq i \leq c
\end{cases}
\]

where
\begin{itemize}
  \item \(x\): sample
  \item \(v\): clustering center
  \item \(n\): number of sample
  \item \(c\): number of clusters \((1 < c < n)\)
  \item \(m\): fuzzy factor
  \item \(d_{ij}\): distance between \(x_j\) and \(v_i\)
  \item \(U\): matrix of \(c \times n\)
  \item \(V\): matrix of \(c \times n\)
\end{itemize}

The minimization problem for the fuzzy clustering can be solved by the following procedures.

**Step 1:** initialization, \(y^{(0)}\)

Let \(k = 0\); select \(\varepsilon\)

**Step 2:** Calculation of \(U^{(k)}\)

* If \(\forall j, r, d_{jr}(k) > \varepsilon\), then
  \[
u_j = \frac{1}{\sum_{r=1}^{c} \left(\frac{d_{jr}(k)}{d_{jr}(k)}\right)^{2m-1}}
  \]

* If there exist \(j, r\), such that \(d_{jr}(k) = 0\), then
  \[u_{jr}(k) = 1\] and \[u_{jr}(k) = 0\] for \(i \neq r\)

**Step 3:** Calculation of \(V^{(k+1)}\)
\[
V_i(t+1) = \frac{\sum_{j=1}^{n} w_{ij} v_j(t) x_j}{\sum_{j=1}^{n} w_{ij} v_j(t)}
\]

**Step 4:** Stopping criteria

Stop if \( |v_i^{(k-1)} - v_i^{(k)}| < \epsilon \)
Otherwise, go to step 2

**RESULTS AND APPLICATION**

This section presents the description of data used for the derivation of RSL. Vehicle classification results from the developed heuristic discriminant algorithm and clustering results by FCM are presented with the application of the proposed methodology.

**Data**

The data used in this study were collected from the Traffic Detection and Surveillance Sub-tested (TDS) on the I-405 northbound freeway in Irvine, California. The 0.7-mile freeway section contains two contiguous detection stations equipped with double inductive loop detectors. Vehicle signature data are extracted in real-time by high-speed scanning loop detector cards and stored in dedicated computers in the field. In addition, overhead vertical-mount video cameras were installed over each lane of traffic and were connected to a ground-ruthing video image processing system. In addition, both radar detectors and acoustic detectors were installed. Figure 4 shows the configuration of TDS on the I-405 northbound freeway.

Communications between the upstream and downstream sites is by dedicated high-speed wireless Ethernet, with fiber optic cable between the downstream mainline cabinets and the ramp cabinet. Wireless Ethernet is also used to communicate from the downstream site to a City of Irvine cabinet where data enters the City network and is sent to the University of California, Irvine (UCI) testbed labs and UCI data and web server, as well as the internet.

Inductive vehicle signature data from two time periods including peak hours during four days in October 2002, for 06:00-10:00 am and 15:00-20:00 pm, were used for this study. A total of 24 hours of data resulted, excluding time periods that were not available due to communication problems in the field, and resulted in 136,817 car-following events, which were used to derive the RSLs.
Vehicle classification

2,486 vehicles collected on the freeway were used to develop the heuristic discriminant algorithm for vehicle classification. Ground-truthed data based on the visual inspection were prepared to investigate the performance of the algorithm. Figure 5 shows the developed classification algorithm providing promising results with an 82.02% correct classification rate. More detailed classification results based on vehicle types are presented in Table 2.

<table>
<thead>
<tr>
<th>Group</th>
<th>Vehicle Type</th>
<th>Total Vehicle Number</th>
<th>Correct Classified Number</th>
<th>Correct Classification Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group1</td>
<td>Motorcycle</td>
<td>4</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>Group2</td>
<td>Passenger Car / Mini Van</td>
<td>1,370</td>
<td>1,126</td>
<td>82.19</td>
</tr>
<tr>
<td>Group3</td>
<td>Sport Utility Vehicle</td>
<td>474</td>
<td>327</td>
<td>68.99</td>
</tr>
<tr>
<td>Group4</td>
<td>Van/ Small Pickup Truck</td>
<td>504</td>
<td>449</td>
<td>89.09</td>
</tr>
<tr>
<td>Group5</td>
<td>Truck / Bus</td>
<td>80</td>
<td>79</td>
<td>98.75</td>
</tr>
<tr>
<td>Group6</td>
<td>Trailer</td>
<td>54</td>
<td>54</td>
<td>100</td>
</tr>
</tbody>
</table>

|                |                               | 2,486                | 2,039                      | 82.02                           |
Clustering results

RSIs obtained over 5-minute aggregation intervals were used as inputs for the FCM clustering algorithm. One major issue arising from clustering analysis is how many groups would be the most appropriate for the given purpose. To determine the optimum number of groups, we used Wilk’s lambda ($\Lambda$) defined as the ratio of within-groups variance to total variance. A lower Wilk’s lambda represents better clustering (7).

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

where, $W$ = pooled within-groups variance  
$B$ = between groups variance  
$T$ = total variance

Because applying the larger number of groups produces lower Wilk’s lambda, we should decide the proper number of groups that can be effectively used to evaluate traffic safety. As we can identify in the clustering results shown in Figure 6, significant marginal improvement due to a decreasing value of Wilk’s lambda is not observed after 6 groups, which means the most appropriate number of clusters corresponding to S-LOS criteria for
the data used is 6. Based on the results, real-time S-LOS criteria for freeway safety can be stated in terms of RSI averaged over the 5-minute interval as shown in Table 3.

![Figure 6 FCM clustering results](image)

Table 3 Real-time Safety-based LOS (S-LOS) on freeway

<table>
<thead>
<tr>
<th>S-LOS Category</th>
<th>S-LOS Criteria (RSI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>≤ 0.251</td>
</tr>
<tr>
<td>B</td>
<td>&gt; 0.251 and ≤ 0.306</td>
</tr>
<tr>
<td>C</td>
<td>&gt; 0.306 and ≤ 0.355</td>
</tr>
<tr>
<td>D</td>
<td>&gt; 0.355 and ≤ 0.416</td>
</tr>
<tr>
<td>E</td>
<td>&gt; 0.416 and ≤ 0.510</td>
</tr>
<tr>
<td>F</td>
<td>&gt; 0.510</td>
</tr>
</tbody>
</table>

S-LOS A describes very safe traffic conditions with low RSI up to 0.251. Even if a traffic accident occurs under this level of service, the possibility of subsequent accident occurrences by not maintaining safety distances would be expected to be much lower than any other level of service. On the other hand, S-LOS F describes traffic safety on freeway with RSI in excess of 0.510. Traffic conditions under this level of service can be described as very unsafe leading to the highest possibility of subsequent accident occurrences based on the proposed S-LOS.

Application

To illustrate the application of the results in Table 3, RSI was computed over the 5-minute aggregation interval using the actual data. In an on-line situation, the RSI would be calculated for each given time interval, and then assigned an appropriate S-LOS from Table 3. This is illustrated in Figure 7.
In practice, a field computer to collect inductive vehicle signatures could derive RSI and determine S-LOS. The S-LOS determined for each given time period could be communicated in real-time to the operating agency’s traffic management center, either for direct safety evaluation, or as input to other software applications for developing countermeasures to prevent accident occurrence.

CONCLUSION

The most innovative feature of this study is to develop a methodology for evaluating real-time traffic safety on freeways. Unlike most existing studies focusing on assessing traffic mobility, efforts devising a new safety performance index were performed in this study.

To overcome the limitations associated with the use of actual accident data for evaluating real-time traffic safety on freeways, this study proposed a new methodology incorporating a traffic conflict technique and an advanced ILD-based surveillance system. The proposed surveillance system utilizing inductive vehicle signatures allows us to obtain individual vehicle information with comparatively lower costs owing to using the existing loop infrastructure. Individual vehicle information such as vehicle arrival time, speed, length, and some other valuable features were used for deriving the proposed real-time safety index (RSI) based on the safety distance in the car-following situation, which is potentially related with freeway rear-end traffic collisions.
In this study, a Fuzzy C-means clustering algorithm was employed to categorize RSIs in order to effectively identify the level of safety. Clustering results showed that 6 categories were most appropriate for safety-based LOS criteria.

It is believed that the proposed methodology for evaluating real-time safety performance on freeways could a valuable tool to operating agencies in support of countermeasure development to prevent accident occurrence. Furthermore, the information could be used for real-time traveler information.

REFERENCES