Network-level Inconsistency based Models for Macro-level Safety Evaluation

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Abstract

Geometric design consistency is the conformance of road geometry with driver's expectation. Studies have identified different consistency measures understanding the driver-vehicle-infrastructure interactions, and these are important surrogate measures for safety analysis. The most common among these is speed-based inconsistency. Though the micro-level impact of inconsistency on road safety is widely explored, the macro-level safety evaluation, this study considers the spatial spread of speed-based local inconsistency in a road network and evaluation using inconsistency as a factor is yet to be analysed. To better analyse the impact of the spread of inconsistency, a spatial unit is defined based on homogeneity of local inconsistency. The spread of local inconsistency quantified as speed variation at every curve-tangent and curve-curve transition in the network is spatially clustered to define the spatial unit of safety analysis. Two network-level inconsistency measures are then computed for these regions, and are used to model crash frequency in these regions. Network level inconsistency measure together with network structure present significant effect on macro-level road safety. Results indicate the applicability in inconsistency and network structure in identifying macro-level hotspots in road networks.

Keywords: Network-level inconsistency; Macro-level safety; Spatial partitioning; Operating speed; Crash modeling

1. Introduction

Driving involves the interaction of infrastructure with the driver. The disharmony in this interaction have been recently evaluated using geometric design inconsistency, which relates driver's expectancy and road infrastructure. The impact of different inconsistency measures has been reported in safety studies, among which the most commonly used is speed-based inconsistency [1,2,3,4,5,6,7] since speed is a collective representation of several factors on the road. Though inconsistency have been identified as a potential factor in crash analysis at local scale, its impact in terms of its spread at network scale has not been explored. This study evaluates the influence of network scale inconsistency measure on macro-level road safety.

For macro-level safety analysis, an important issue of spatial model is the choice of certain level of spatial unit. Traditional macro-level safety analysis uses spatial units such as traffic analysis zones (TAZ) and census tract, which often fails the criteria of spatial homogeneity w.r.t variable and this aggregation level significantly affects the model performance. Therefore, the decision of spatial unit should be done based on the scope of the study. For example, to analyze the significance of traffic in road safety, Wang et al. [8] developed a new spatial unit based on traffic density homogeneity. The results proved the inevitability of homogeneity of traffic characteristics in the spatial unit to capture the significance of traffic in crash occurrence. Thus, to reduce the error due to ecological fallacy and to get a reliable inconsistency measure at network scale, an appropriate spatial partitioning approach should be employed to define the spatial unit, such that the spatial homogeneity in inconsistency is ensured. This study presents two objectives of defining the spatial unit for macro-level safety analysis and analyzing the impact of network-level inconsistency in road safety.

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2. Methodology

Different spatial partitioning methods such as k-mean clustering, regionalization with dynamically constrained agglomerative partitioning, normalized cut minimization etc. [8,9,10] have been employed in road safety studies for the aggregation of spatial levels. Here, to divide the network into regions, spatially constrained hierarchical clustering (SCHC) with contiguity constraints is adopted. Two spatially contiguous entities with lowest dissimilarity are clustered, and the dissimilarity matrix and contiguity matrix are updated each time a new merge unit is formed. The dissimilarity matrix is defined using the inconsistency measure in the network. Operating speed-based inconsistency is a reliable indicator of crash occurrence and is commonly adopted in road safety studies. In the present study, the network is segmented based on curvature, and the local inconsistency at every tangent-curve and curve-curve transition quantified as maximum of variation of speed (ΔV_{85}) at transition in both direction of travel.

As network-level inconsistency estimate, we propose two measures; a) average of inconsistency in the region ($\bar{I}$) and b) inconsistency density in the region (ID_{10}). Average inconsistency in the region is calculates as the average of all the inconsistency of the segments in the region, whereas, the inconsistency density is calculated as the density of speed variation greater than 10 kmph in the region.

To account for the unobserved effect of macro-level factors such as demography, traffic operational features, road network structure, we propose the use of network centrality measure as a proxy. Several studies have reported the correlation of network centrality measure with that of land use, traffic and travel demands [11,12,13,14,15]. Edge betweenness centrality captures the importance of each road segment considering it being central and intermediatory. For the present study, a modified access weighted edge betweenness centrality ($\overline{C.A}$) is estimated to incorporate accessibility conditions in the network structure.

3. Analysis and Results

For the macro-level crash analysis using network level inconsistency, the road network consisting of major roads in Thiruvananthapuram district in Kerala state of India is considered. Based on the curvature criteria, the network is segmented into 1429 curves and 745 tangent segments using Road Curvature analyst, a GIS add-in tool developed by Bil et al. [16]. Due to unavailability of speed prediction data applicable at network scale, this study resorts to crowd-sourced speed from Google map. The geocoded crash data was provided by Road safety authority, which was further filtered to obtain crash data specific to major roads. Using SCHC, the network segments are clustered to form 64 network regions. A Moral I value of 0.66 with a p-value of 0.01 indicated that the data has been significantly and well clustered.

Due to the overdispersion property of crash count data, the negative binomial is widely adopted for crash modeling. [17,18,19,20]. Here, a negative binomial model is used to predict crash frequency in the regions defined. As a preliminary analysis, the correlation trend of inconsistency measures with crash count was analyzed using scatter plot, which represented linear trend for average inconsistency and inverse relation with inconsistency density as depicted in Figure 1a and 1b respectively. The scatter plot suggests the presence of unobserved variable. Therefore, to account for this, network variable is considered along with each of the inconsistency measure. Two developed models namely model I and model II with significance of variables and model goodness of fit statistics are presented in Table 1. Goodness of fit of model was assessed using Pearson's χ^2 statistics, log-likelihood chi-square, and Akaike's Information Criteria (AIC). Both Pearson's χ^2 statistics, log-likelihood chi-square represent good fit and AIC value when compared suggest model with inconsistency density and weighted betweenness as more significant.

4. Discussion

The association of inconsistency with crash occurrence is evident from the signs and significance of coefficients of inconsistency measures in models I and II. The modified inconsistency with weighted betweenness measure indicates increase in crash count as both betweenness and inconsistency increase. This implies that, a region with driving instances of high-speed variation, high accessibility and highly central road are highly vulnerable to crash occurrence. Whereas, the model estimates with inconsistency density represents negative association of inconsistency with crash occurrence. This suggest that rare occurrence of high-speed variation affect driver expectancy.

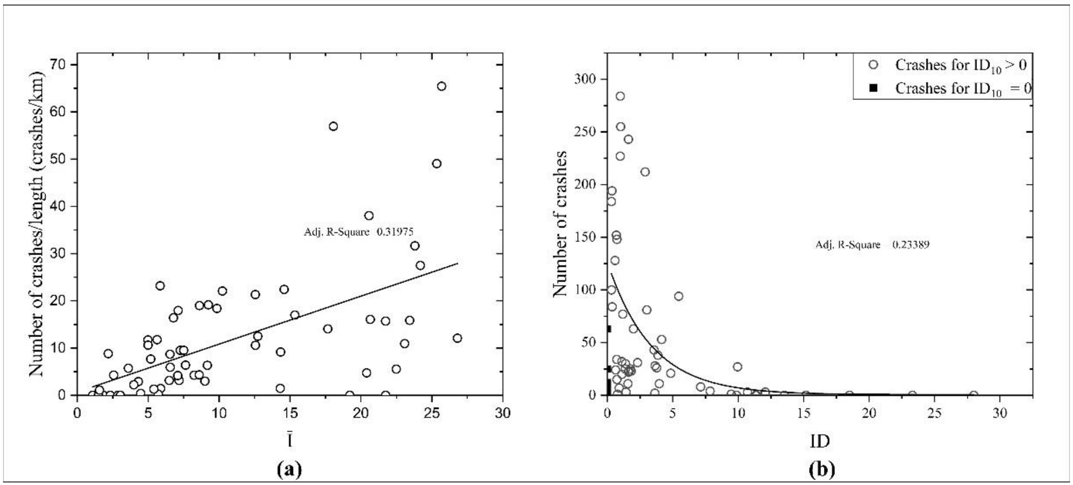

Figure 1. Scatter plots of crashes in network regions against: (a) average inconsistency and (b) inconsistency density

Table 1: Crash frequency models with network-level inconsistency variables

Model I :	$Y_i = e^{\beta_0} . e^{\beta_1 . \bar{I} . \overline{C.A}}$	
Variable	Estimates	Sig.
(Intercept)	3.064	0.000
$\bar{I}.\overline{C.A}$	0.063	0.000
Pearson χ^2	93.071	
$\chi^2_{(0.001)}$	102.15	
Log-likelihood Chi-square	61.269	0.000
Log-likelihood	-295.885	
AIC	595.769	
Model II :	$Y_i = e^{\beta_0} . e^{\beta_1 . ID_{10} + \beta_2 . \overline{C.A}}$	
(Intercept)	4.115	0.000
ID_{10}	-0.276	0.000
$\overline{C.A}$	0.376	0.000
Pearson χ^2	81.549	
$\chi^2_{(0.001)}$	100.881	
Log-likelihood Chi-square	94.818	0.000
Log-likelihood	-281.145	
AIC	568.290	

5. Conclusion

The study presents a methodology for macro-level safety evaluation considering network-level design inconsistency measures. The macro-level empirical analysis indicates that all instances of high variation in speed need not be crash inducive. Models indicate that the impact of inconsistency on road safety is interlinked with the network structure of the region. Results infers that high variation of speed in region of highly accessible and central roads leads to crash occurrence. Similarly, the inconsistency density within a region also plays a crucial role in safety assessment. This measure reflects the driver expectation acquisition phenomenon at a macro scale. For example, a driver would pre-conceive the presence of frequent sharp curve on a road network in hilly regions, making the traverse free of surprises. The regional trends of crash occurrence based on the inconsistency in the region can be a promising application to practitioners in identifying macro-level hotspots.

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