Incorporating a Safety Index into Pathfinding

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Travelers around the world are concerned with choosing not only the quickest route from one point to another but also the safest route. Traffic safety has always been a major public concern, and traffic safety performance should be constantly evaluated so that both reactive and proactive countermeasures can help reduce crashes. This study developed a methodology for incorporating safety aspects into travelers' pathfinding process. The safe pathfinding process included two main parts: a route-specific safety hazard index and a route-finding algorithm that considered both travel time and safety. The ratio of the deceleration rate to avoid a crash to the maximum available deceleration rate was chosen as the proxy for traffic safety. The safety hazard index was formulated by using the collision mechanism along the roadway segment and at the intersection. Motorist-specific information (e.g., vehicle type, age, pavement condition) was also included in the safety index model so that a traveler's individual needs could be considered. The pathfinding algorithm, which combined mobility and safety, had three objectives: shorter travel time, lower route safety hazard index, and avoidance of sites with the highest safety hazard index along the route. The methodology was applied in a real-world street network to demonstrate its use and prove the concept of finding a safe path.

Traffic safety concerns have increased around the world. According to NHTSA's traffic facts, more than 6 million crashes were reported in the United States in 2014; they resulted in more than 32,000 fatalities and 2 million injuries (*1*). Traffic crashes rank third when it comes to years of life lost, just behind cancer and heart disease (*2*). Collision avoidance systems, which integrate radar-assisted technologies, have been increasingly adopted as a way to reduce crashes (*3*). Aside from advanced vehicular technologies, a large number of studies have been dedicated to the evaluation of road traffic safety. Various crash prediction models and surrogate safety measures have been developed to help identify crash-prone conditions (*4*) and find appropriate countermeasures to protect travelers.

Vehicle routing assistance has commonly been used to help travelers find the optimal route based on distance, travel time, travel costs, or all three (*5*). Unlike travel time or distance, crash risk has not been seriously considered as a vital factor in selecting a preferred route (*3*). Although navigation applications like Waze have started to incorporate traffic safety in their navigation applications by minimizing dangerous left turns at busy intersections, the process remains in its infancy and lacks a systematic method (*6*). It is necessary to develop a valid and easy-to-implement route safety indicator to incorporate traffic safety into vehicle routing.

This study aims at developing a methodology for comprehensive routing with simultaneous consideration of both mobility and safety. A two-step procedure was proposed: first, an easy-to-implement safety hazard index with very few data requirements was developed for the pathfinding method; next, the process was used to select a route based on travel time and the proposed safety index. The proposed procedure was tested with a real-world street network.

LITERATURE REVIEW

Incorporating safety into the routing decision is a relatively new concept (*3, 7*). The biggest obstacle is figuring out how to use the limited data to develop an index that can accurately measure the safety performance along a route (*3, 7*). Kingsbury et al. conducted an exploratory study on the journey optimization for the safest route (*7*); they compared two safety indicators: a risk prediction model that adopts regression models to estimate the crash rate based on physical and operational variables (e.g., intersection type and traffic volume) and a model that relies on historical crash records to predict crash rate. The study found that the method based on crash history is more reliable. Kingsbury et al. also determined that risk prediction methods always suggest that drivers avoid high-volume roads because these roads are assumed to have a higher crash risk; however, this assumption is often the opposite of reality. Many roads in the study by Kingsbury et al. with higher annual average daily traffic were actually associated with a lower number of crashes. Chandra proposed a complete framework for safety-based pathfinding methods; it focused specifically on older drivers and bicyclists (*3*). The study used the time-to-collision index, which, although it is a commonly used safety indicator, is limited by many assumptions made to overcome unavailable roadway attributes and traffic conditions along the link or around the intersection. Moreover, Chandra's method cannot be comprehensively validated. Another application, the safety indicator for school bus routing, includes crash records and manual evaluation of safety aspects of each link and intersection (*8*). Different criteria such as geometrical characteristics, lighting, and signage are manually assigned a score. The total safety score is the summation of the weighted score for each criterion.

One way to integrate safety into the routing algorithm is to solve a resource-constrained shortest-path problem. A variation of this solution, which is discussed in the study by Kingsbury et al., involves the weighting system for safety and travel time (*7*). Travelers can choose their own preference on how much safety and travel time will be factored into to the shortest route. An alternative approach is the multiobjective shortest-path algorithm. Chandra proposed a

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Transportation Research Record: Journal of the Transportation Research Board, No. 2659, 2017, pp. 63–70.
http://dx.doi.org/10.3141/2659-07

modified form of the multiobjective shortest-path method based on the median shortest-path problem (*3*). Although both methods were effective in finding safe routes, safety is treated as a constraint in the resource-constrained shortest-path problem but as an objective in the multiobjective shortest-path problem (*3, 7*).

In general, three types of factors affect traffic safety: human factors (e.g., age, gender), road and environmental factors (e.g., lighting condition, time of day, pavement condition, road geometric design, traffic characteristics), and vehicle factors (e.g., maximum deceleration rate) (*9*). The factors can be used collectively to develop an approach for generating a safety index. Figure 1 shows four approaches for measuring traffic safety: historical crash records, crash prediction models, safety scores, and surrogate measures (*4, 10–17*).

Historical crash records are the most straightforward safety assessment indicator. The random and sparse nature of traffic accidents means that more data need to be collected to measure road safety conditions (*4*). A small number of crash records usually offer limited information on traffic safety. Crash prediction model development requires a comprehensive data set (intersection features, road segment features) to predict expected crash frequency. However, driver behavior—one of the main causes of crashes—is left out of most data sets (*15*). The safety score, when compared with crash data and crash models, is a more subjective approach, in which scores are given based on a series of criteria (*8, 17*). A safety score can be assigned to individual traffic facilities (e.g., road segment, intersection) or to the entire route. Dijkstra calculated scores for each route by using proposed criteria such as minimized transitions between road categories, minimized number of left turns, and intersection density as low as possible (*17*).

Safety surrogate measures can be calculated directly from microsimulation models or developed from collision mechanisms (*4, 10–12, 14–16*). The outstanding issue with surrogate measures calculated from a microsimulation model is that traffic always obeys the traffic rules in this model. Obviously, this characteristic contradicts real-world situations, since some crashes occur because of the violation of traffic laws (*4*). Moreover, obtaining the index from a microsimulation model for routing purposes requires a huge computational effort. Surrogate measures developed on the basis of collision theory, however, can be categorized as time-based, deceleration-based, and so on (*4*). The typical time-based measure is time to collision, which was used by Chandra to find the safest route (*3*). However, the time to collision assumes that speed does not change until a collision occurs, and this assumption neglects the possibility of deceleration. In contrast, the deceleration rate measure (DRAC) does consider the possibility of deceleration when there is the risk of a collision (*4, 14*). Surrogate measures such as time exposed and time to collision integrate temporal characteristics into traditional surrogate measures (*4*). Advantages and disadvantages of all these methods should be carefully reviewed when a new methodology for a safety index is proposed.

METHODOLOGY

A safety index or a safety hazard index for routing should be easy to implement and be able to handle data limitations. Therefore, a novel safety index is proposed (Figure 2) that requires only road traffic density data and speed data.

Of all the safety surrogate measures discussed, DRAC has the minimum deceleration rate required to avoid a collision with the leading vehicle and also has the maximum available deceleration rate (MADR) that a vehicle can adopt (*14*). It is assumed that a crash would happen if the DRAC exceeds the MADR. The MADR can be determined by multiple factors, including vehicle type (vehicle weight), pavement condition (dry or wet), and so on (*14*). A safety hazard index can be expressed as the ratio of DRAC to MADR; a lower value indicates a safer road. Two kinds of data are required to determine this index: the existing road information such as link traffic density and average link speed and traveler information, which allows the index to vary by user. Respective indexes are used for links and intersections based on crash mechanism. An index is proposed for different turning movements at an intersection (left turn, through turn, and right turn).

Safety Hazard Index for Roadway Link

The most common cause of a rear-end crash, the sudden braking of the lead vehicle, was considered for simplicity. It is supposed that the subject Vehicle A and its preceding Vehicle B operate in

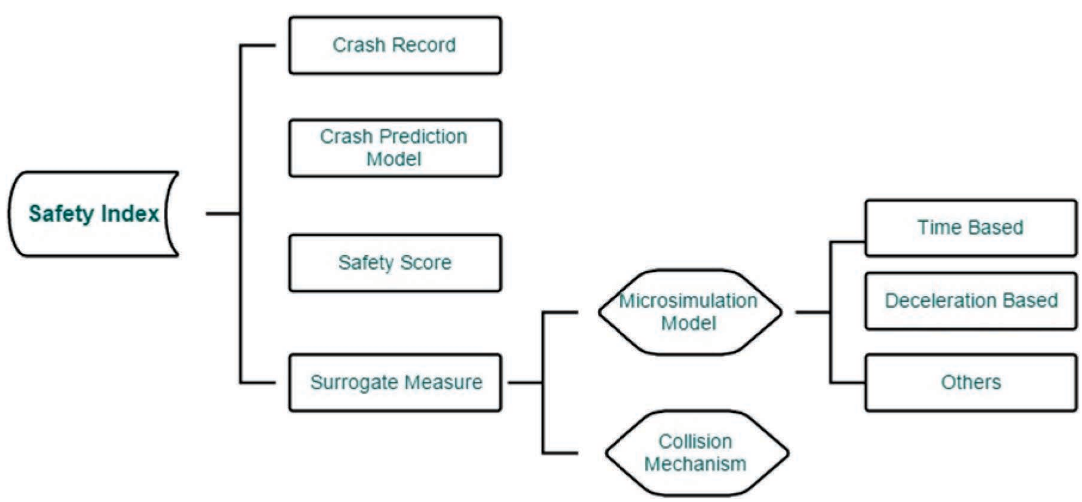

FIGURE 1 Summary of safety assessment methods.

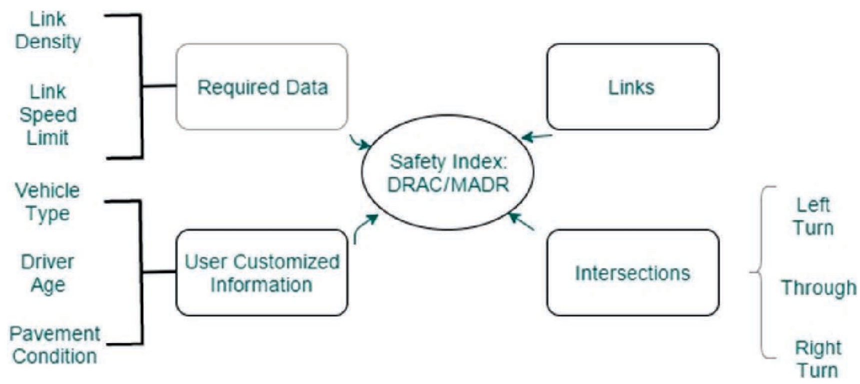

FIGURE 2 Framework of proposed methods.

the same lane with the speed of v_A and v_B, respectively. Suddenly, the leading Vehicle B stops, and its speed becomes zero. D_L is the expected closest distance between the two consecutive vehicles, Δt is the perception–reaction time for the driver in the following vehicle (Vehicle A). Human behavior such as driver inattention, impairment, and distraction are not considered. Then DRAC for Vehicle A can be formulated as follows:

$$\text{DRAC}_A = \frac{v_A^2}{2(D_L - v_A \Delta t)} = \frac{v^2}{2(D_L - v\Delta t)} \tag{1}$$

where v_A can be estimated by the average link speed v.

The index is calculated as the ratio of DRAC_A to MADR_A. If the subject Vehicle A is the lead vehicle, the DRAC for Vehicle B is exactly the same as it is for Vehicle A; however, MADR_B may be different. Therefore, the larger value of the two is considered as the safety hazard index for the link.

In Equation 1, the expected closest distance between the two successive vehicles D_L is unknown. Two traffic density scenarios (sparse and dense) are proposed to calculate this distance (*3*). The density of 50 vehicles per mile per lane was used to distinguish the two traffic states. The number of arrival vehicles along the link in a sparse traffic state is assumed to follow a Poisson distribution (*18*); thus, the gap between two consecutive vehicles follows a negative exponential distribution:

$$f(s) = de^{-ds} \tag{2}$$

where s is the distance between two successive vehicles on the same lane, and d is the vehicle density along the link.

The expected closest distance D_L is calculated as follows:

$$D_L = \int_{s=0}^{s=l} sf(s)\,ds = \int_{s=0}^{s=l} sde^{-ds}ds = \frac{1}{d}\left(1 - e^{-dl} - dle^{-dl}\right) \tag{3}$$

where l is the link length.

The distance between two consecutive vehicles in a dense traffic state is assumed to follow the Gaussian unitary ensemble distribution (*19*), as follows:

$$f(s) = \frac{32s^2d^3}{\pi^2} e^{\frac{4s^2d^2}{\pi}} \tag{4}$$

The expected closest distance D_L is

$$D_L = \int_{s=0}^{s=l} sf(s)ds = \int_{s=0}^{s=l} \frac{32s^3d^3}{\pi^2} e^{-\frac{4s^2d^2}{\pi}} ds = \frac{1}{d}\left(1 - \frac{4l^2d^2}{\pi} e^{-\frac{4l^2d^2}{\pi}} - e^{-\frac{4l^2d^2}{\pi}}\right) \tag{5}$$

The expression of the safety hazard index I_{link} for any link is

$$I_{\text{link}} = \max\left\{\frac{\text{DRAC}_A}{\text{MADR}_A}, \frac{\text{DRAC}_B}{\text{MADR}_B}\right\} = \max\left\{\frac{\dfrac{v^2}{2(D_L - v\Delta t)}}{\text{MADR}_A}, \frac{\dfrac{v^2}{2(D_L - v\Delta t)}}{\text{MADR}_B}\right\} \tag{6}$$

where

$$D_L = \begin{cases} \dfrac{1}{d}\left(1 - e^{-dl} - dle^{-dl}\right) & \text{for sparse traffic conditions} \\ \dfrac{1}{d}\left(1 - \dfrac{4l^2d^2}{\pi} e^{-\frac{4l^2d^2}{\pi}} - e^{-\frac{4l^2d^2}{\pi}}\right) & \text{for dense traffic conditions} \end{cases}$$

Safety Hazard Index at Intersections

The intersection-related crash is more complicated than the link-based crash, since there are several types of intersections (uncontrolled, stop controlled, signal controlled) and collisions can occur in various situations (stop control violation, signal violation, conflict between left-turn flow and approaching flow, etc.). It is not practical, because of data limitations, to develop indexes for different intersections. Figure 3 presents a typical angle collision process irrespective of intersection type. For simplicity, only angle collisions are discussed.

Suppose that there is subject Vehicle A and another, Vehicle B, which is the closest to A around the intersection on the other leg approach with speeds of v_A and v_B, respectively. Two crash scenarios are considered: (*a*) Vehicle B decelerates but fails to avoid colliding with Vehicle A, and (*b*) Vehicle A decelerates but still collides with Vehicle B. In Figure 3, measured from Time Point 1, the initial

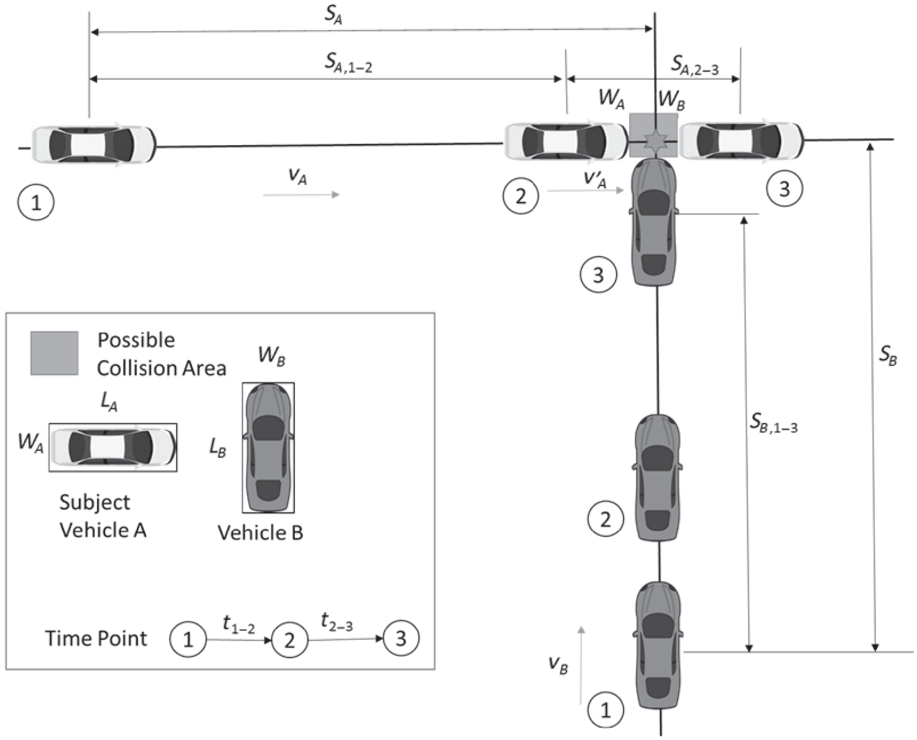

FIGURE 3 Vehicle collision modeling at intersection (L_A = length of subject Vehicle A; L_B = length of other Vehicle B; W_A = width of subject Vehicle A; W_B = width of other Vehicle B).

distance from Vehicle A and Vehicle B to the intersection is S_A and S_B, respectively. The sum of S_A and S_B is D_I, defined as the expected closest distance between two vehicles around the intersection. Vehicle B is assumed to decelerate while Vehicle A maintains the same speed before reaching the intersection or the possible collision area (Time Point 2). The possible collision area is determined by the length and width of the approaching vehicles. To obtain the DRAC, a critical time point when Vehicle A leaves the collision zone and Vehicle B enters the area is proposed (Time Point 3). The time interval between Time Points 1 and 2 is

$$t_{1-2} = \frac{S_{A,1-2}}{v_A} = \frac{S_A - \dfrac{L_A + W_B}{2}}{v_A} \tag{7}$$

where

$S_{A,1-2}$ = distance A travels from Time Point 1 to Time Point 2,
W_B = width of other Vehicle B,
W_A = width of subject Vehicle A,
L_B = length of other Vehicle B, and
L_A = length of subject Vehicle A.

When Vehicle A enters the intersection, the speed may change (noted as v'_A). For a left-turn movement, the vehicle's speed will significantly decrease. The time interval between Time Points 2 and 3 is expressed as follows:

$$t_{2-3} = \frac{S_{A,2-3}}{v'_A} = \frac{L_A + W_B}{v'_A} \tag{8}$$

where $s_{A,2-3}$ is the distance A travels from Time Point 2 to Time Point 3.

Under the critical situation in which Vehicle B does not collide with Vehicle A, the distance Vehicle B travels from the start of deceleration to the time Vehicle A leaves the collision zone (from Time Point 1 to Time Point 3) is expressed as follows:

$$\begin{aligned} S_{B,1-3} &= v_B \Delta t + v_B (t_{1-3} - \Delta t) - \frac{1}{2}\mathrm{DRAC}_B (t_{1-3} - \Delta t)^2 \\ &= v_B t_{1-3} - \frac{1}{2}\mathrm{DRAC}_B (t_{1-3} - \Delta t)^2 \end{aligned} \tag{9}$$

where

$$t_{1-3} = t_{1-2} + t_{2-3} = \frac{S_A - \dfrac{L_A + W_B}{2}}{v_A} + \frac{L_A + W_B}{v'_A}$$

is the time interval between Time Points 1 and 3, and Δt is the perception–reaction time of the driver to decelerate.

The minimum value of S_A is $(L_A + W_B)/2$, or t_{1-2} is nonnegative in Equation 7. Thus,

$$\begin{aligned} 0 < S_{B,1-3} &\le D_I - \min(S_A) - \frac{L_B + W_A}{2} \\ &= D_I - \frac{L_A + W_B}{2} - \frac{L_B + W_A}{2} = D_I - \frac{L_A + W_B + L_B + W_A}{2} \end{aligned} \tag{10}$$

Given the assumption that vehicles are randomly distributed along the street, the expected value of $S_{B,1-3}$ equals

$$\frac{1}{2}\left(D_I - \frac{L_A + W_B + L_B + W_A}{2}\right)$$

Replace $S_{B,1-3}$ in Equation 9 and DRAC for Vehicle B can be expressed as follows:

$$\mathrm{DRAC}_B = \frac{2v_B t_{1-3} - \left(D_I - \frac{\sum L}{2}\right)}{(t_{1-3} - \Delta t)^2} \tag{11}$$

where

$$t_{1-3} = \frac{\frac{1}{2}\left(D_I - \frac{3L_A + 3W_B - L_B - W_A}{2}\right)}{v_A} + \frac{L_A + W_B}{v_A'} \quad \text{and}$$

$$\sum L = L_A + W_B + L_B + W_A$$

If Vehicle A decelerates to avoid the collision, the DRAC for Vehicle A can be calculated by exchanging A and B in Equation 11:

$$\mathrm{DRAC}_A = \frac{2v_A t_{1-3}' - \left(D_I - \frac{\sum L}{2}\right)}{(t_{1-3}' - \Delta t)^2} \tag{12}$$

where

$$t_{1-3}' = \frac{\frac{1}{2}\left(D_I - \frac{3L_B + 3W_A - L_A - W_B}{2}\right)}{v_B} + \frac{L_B + W_A}{v_B'}$$

and v_B' is the speed of B around the intersection.

In both Equations 11 and 12, D_I, the expected closest distance between two vehicles around the intersection, is unknown. According to Chandra (*3*), a similar assumption can be made that vehicles around the intersection are uniform randomly distributed under light traffic conditions; this assumption means that the probability of n vehicles around the intersection is

$$P(N = n) = \frac{(ds)^n e^{-ds}}{n!} \tag{13}$$

where

- N = random number of vehicles around intersection,
- s = total link-based distance around intersection (sum of lengths of streets converging to intersection), and
- d = vehicle density around intersection (number of vehicles per unit length).

The probability that subject Vehicle A misses a vehicle within the total distance s around the intersection is the probability when $n = 0$, namely, $P(N = 0) = e^{-ds}$. Then the expected closest distance around the intersection D_I is calculated as

$$D_I = \int_{s=0}^{s=L} s\left(1 - P(N = 0)\right)' \, ds = \int_{s=0}^{s=L} s d e^{-ds} \, ds = \frac{1}{d}\left(1 - e^{-dl} - dl e^{-dl}\right) \tag{14}$$

where L approximately equals the summation of the length of all street legs around the intersection ($L \approx \Sigma^l$).

For dense traffic conditions, the link-based distance between two consecutive vehicles around the intersection is assumed to follow a Gaussian unitary ensemble distribution (*3*) and is formulated as follows:

$$f(s) = \frac{32 s^2 d^3}{\pi^2} e^{-\frac{4s^2 d^2}{\pi}} \tag{15}$$

The expected closest distance D_I is expressed in Equation 16:

$$D_I = \int_{s=0}^{s=L} s f(s) \, ds = \int_{s=0}^{s=L} \frac{32 s^3 d^3}{\pi^2} e^{-\frac{4s^2 d^2}{\pi}} \, ds = \frac{1}{d}\left(1 - \frac{4L^2 d^2}{\pi} e^{-\frac{4L^2 d^2}{\pi}} - e^{-\frac{4L^2 d^2}{\pi}}\right) \tag{16}$$

In summary, the safety index for each intersection is

$$I_{\text{intersection}} = \max\left\{ \frac{\frac{2v_A t_{1-3}' - \left(D_I - \frac{\sum L}{2}\right)}{(t_{1-3}' - \Delta t)^2}}{\mathrm{MADR}_A}, \frac{\frac{2v_B t_{1-3} - \left(D_I - \frac{\sum L}{2}\right)}{(t_{1-3} - \Delta t)^2}}{\mathrm{MADR}_B} \right\} \tag{17}$$

where

$$D_I = \begin{cases} \frac{1}{d}\left(1 - e^{-dl} - dl e^{-dl}\right) & \text{for sparse traffic conditions} \\ \frac{1}{d}\left(1 - \frac{4L^2 d^2}{\pi} e^{-\frac{4L^2 d^2}{\pi}} - e^{-\frac{4L^2 d^2}{\pi}}\right) & \text{for dense traffic conditions} \end{cases}$$

$$t_{1-3}' = \frac{\frac{1}{2}\left(D_I - \frac{3L_B + 3W_A - L_A - W_B}{2}\right)}{v_B} + \frac{L_B + W_A}{v_B'}$$

$$t_{1-3} = \frac{\frac{1}{2}\left(D_I - \frac{3L_A + 3W_B - L_B - W_A}{2}\right)}{v_A} + \frac{L_A + W_B}{v_A'}$$

$$\sum L = L_A + W_B + L_B + W_A$$

The safety index for right-turn movements at the intersection is assumed to be zero because the right-turning vehicle is unlikely to be involved in an angle collision. The difference for through and left-turn movements can be simplified to be the speed for the subject vehicle when it enters the intersection. For a through movement, it is assumed that $v'_A = v_A$. When the vehicle makes a left turn, it has to slow down and 15 mph is assumed to be the speed. The turning movement is only considered for subject Vehicle A. For Vehicle B, v'_B is assumed to be v_B.

Review of Safety Hazard Index

Default values for the user-customized variables are considered when the safety index is applied. The perception–reaction time uses 2 s as the average value for older drivers (>51 years old) and 1 s for younger drivers (*20*). According to the Green Book, the design vehicle dimensions for a passenger car are 19 ft × 7 ft and 30 ft × 8 ft for a single-unit truck (*21*). Mean MADR values are adopted from previous research (*22*): 8.45 m/s^2 for a passenger car on dry pavement, 6.82 m/s^2 for a passenger car on wet pavement, 6.34 m/s^2 for a truck on dry pavement, and 5.12 m/s^2 for a truck on wet pavement.

The proposed index was reviewed by qualitatively assessing the relationship between the modeled safety index and the variables in Table 1. An increase in vehicle density increases the safety index because of the increased DRAC for both links and intersections. The relationship between crash rates and traffic density was explained in a previous study (*23*). Previous studies have also proved that vehicle speed increases accident probability (*24*); this relationship is also shown in the index. Intersection speed, also proposed in this index, differentiates between the speeds for different turning movements. Although no study has focused on this speed, the assumption is that higher speed results in less time spent in the intersection, and therefore the probability of a crash is reduced. Perception–reaction time has been shown to be closely related to the minimum stopping sight distance (*25*). Higher perception–reaction time leads to longer stopping sight distance; this value increases the crash rate and coincides with the proposed index. The longer the length of a truck, the more time it takes to cross the intersection, and hence the chance of a collision is increased. Furthermore, it is obvious that the deceleration rate would be lower for trucks and lower on wet pavement; these conditions could also contribute to crash occurrence. Overall, most variables in the proposed model can be validated through previous studies; this validation means that it is a sufficient index for safety assessment.

CASE STUDY

The proposed method was tested in a case study. A multiobjective shortest-path model (which can also consider safety) was utilized instead of a typical route-finding model, which focuses only on the route with the shortest time.

The first objective was to find several routes with shorter travel time. The shortest-route-finding tool in ArcGIS can achieve this goal (*26*). The second objective was to identify a not-inferior solution by balancing both travel time and safety. Most studies sum up the safety index of all links and intersections along one route in order to obtain safety performance information and then select a route based on the safety performance (*3, 7*). Besides consideration of the overall safety performance of the route, the links and intersections with a high safety hazard index were avoided in order to identify the preferred route in the proposed application.

The proposed route-finding method was tested on a street network near the campus of the University of Wisconsin, Milwaukee. The Wisconsin Information System for Local Roads geographic information system map provided information on link traffic volume, speed, and link length for the routing analysis. The speed limit was estimated based on the roadway functional class, and the average link speed was substituted by randomly assigning ±5 mph to the speed limit. Link vehicle density was calculated by using the average daily traffic. One origin and one destination (university campus) were selected. Five candidate routes with short travel time were chosen with ArcGIS (Figure 4).

Route 5 was chosen on the basis of its having the lowest travel time. The safety index was also calculated and compared along these routes. The safety index recommends not-inferior routes depending on the user-customized information. A lower value in the safety hazard index indicates a safer route. Three customized options, "truck," "old," and "wet," which correspond to vehicle type, age, and pavement condition, were also applied. The default options of "passenger car," "young," and "dry" were presented for comparison. The overall safety index and the highest index (worst safety) were calculated for all customized options (Table 2). Route 3 is recommended for truck drivers because it has the lowest overall safety index and avoids the most dangerous route (Route 1). Route 3 is also the best choice for older drivers, wet pavement con-

TABLE 1 Relationship Between Indexes and Variables

		Link		Intersection	
Variable	MADR	DRAC	Safety Index	DRAC	Safety Index
Density (increase)	—	↑	↑	↑	↑
Speed (increase)					
Link speed (increase)	—	↑	↑	↑	↑
Intersection speed (left-turn to through movement: increase)	—	↓	↓	↓	↓
Age (young to old)					
Perception-reaction time (increase)	—	↑	↑	↑	↑
Vehicle type (passenger car to truck)					
Length (increase)	—	—	—	↑	↑
MADR (increase)	↓	—	↑	—	↑
Pavement condition (dry to wet)					
MADR (increase)	↓	—	↑	—	↑

NOTE: — = constant; ↑ = increase; ↓ = decrease.

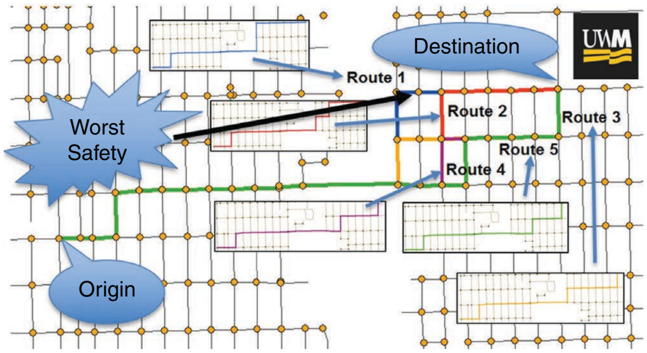

FIGURE 4 Alternative routes.

ditions, and default customer information. Although travel times on Routes 3 and 5 are almost equal, it is much safer to use Route 3 because the summation of all options in the safety index is greatly decreased. Aside from the choice of the safest route, the links or intersections with the worst safety (highest safety index) were also identified. Table 2 shows the dangerous link or node that exists in Route 1 for all four customized options.

CONCLUSIONS AND FUTURE WORK

This study developed a method for incorporating safety into the pathfinding process by developing and applying a novel safety index to the shortest route-finding algorithm. The ratio of DRAC to MADR was adopted as the safety hazard index, in which a lower value indicates a safer condition. The index was formulated on the basis of the collision mechanism along the roadway link and at the intersection. Besides the required roadway information (e.g., link speed, vehicle density), user-specific information (e.g., vehicle type, age, and pavement condition) can be included in the safety index model. A qualitative review of the index, which considers the findings from previous literature, supports the index as a sufficient proxy for traffic safety. A real roadway network was used to apply the proposed safety index. Three objectives were established in the search for the safest and shortest route: shorter travel time, lower overall index, and avoidance of the highest index. Safe routes with different user-customized information were obtained in the application example.

Model assumptions and limitations should be taken into consideration when this index model is applied. The model deals with typical intersections and urban roadways, and not all collision types were considered in developing the index (only rear-end collision and angle collisions were considered). These assumptions were made when the shortest distance between two successive vehicles was acquired, but this result may not always correspond with real-world situations. Future work will expand use of the model to other types of collsions and crash severities and will develop solutions for the multiobjective shortest-path problem. A systematic safe pathfinding method that considers all types of crashes in the safety index is proposed to be built for practical navigation applications in a real-world road network.

TABLE 2 Comparison Between Routes

	Safety Index					
		Option				
Route	Index	Truck	Old	Wet	Default	Travel Time (s)
1	Sum	11.67	13.61	12.19	9.65	234.52
	Highest	1.81	2.03	1.95	1.46	
2	Sum	9.9	12.73	10.31	8.24	236.73
	Highest	0.65	2.03	0.7	0.53	
3	Sum	8.84	10.72	9.15	7.51	232.82
	Highest	0.65	2.03	0.7	0.53	
4	Sum	9.17	11.34	9.51	7.84	238.54
	Highest	0.65	2.03	0.7	0.53	
5	Sum	9.75	12.18	10.12	8.32	232.63
	Highest	0.65	2.03	0.7	0.53	

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The Safety Section peer-reviewed this paper.