Adaptive Personalized Routing for Vulnerable Road Users

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For individuals with special needs such as wheelchair users, mobility is demanding and prevents them from participating in regular social life. In new and unfamiliar places, people with disabilities are overwhelmed by a range of obstacles impeding the easy navigation and access to locations (Ding et al., 2007). According to a survey among wheelchair users, steep slope, narrow sidewalks, inclement weather, bad sidewalk surface and congested cuts are examples of outdoor obstructions that affects their navigation (Meyers et al., 2002). As such, the existing design of navigation systems which mostly determines the shortest path do not entirely fulfill the needs of people with disabilities in terms of mobility and accessibility (Ding et al., 2007; Hahm et al., 2017). Pedestrians with disabilities are more sensitive to accessibility rather than the shortest distance. To address accessibility related issues, it is important for navigation systems to incorporate these factors to handle constraints changing by time. This research proposes a new framework, incorporating a sequential decision making process that allows adaptive navigation in the presence of on-line information. We consider the sidewalk network as a graph $G = (N, E)$, where $n \in N$ is the set of nodes and $e \in E$ is the set of edges. A traveler can move from n and n' if an edge connects the two nodes. We define the cost of each edge e in our network by Equation (1)

$$C_{(e)}(t) = W_w(t)S_{w(e)} + W_l(t)S_{l(e)} + W_s(t)S_{s(e)}S_{wc(e)} + W_{sf}(t)S_{sf(e)}S_{wc(e)} \tag{1}$$

Where $S_w, S_l, S_{wc}, S_s, S_{sf}$ are scores for width, length, weather condition, slope and surface type respectively. We use scores instead of actual values to account for differences in range. The score for S_w, S_l, S_s is obtained by normalizing the actual values. If X is the value of the parameter, the score is given as: $\hat{X} = \frac{X - \min(X)}{\max(X) - \min(X)}$.

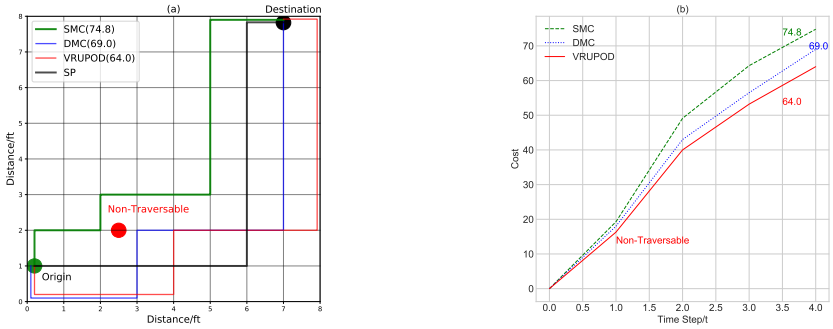
$W_w(t), W_l(t), W_s(t), W_{sf}(t)$ are the time-dependent weights for width, length, slope and surface type. This represents a travelers time-varying preference for each parameter as they progress to

destination and is calculated using the Analytical Hierarchy Process(AHP) where summation of weights at any time t must equal one, written as $W_w(t) + W_l(t) + W_s(t) + W_{sf}(t) = 1$. Five levels of surface type score are considered based on field survey as; (Best) 1: Concrete, 2: Asphalt, 3: Brick, 4: Cobblestone and (Worst) 5: Gravel. Three levels of weather conditions scores are defined as; (Best) 1: Sunny, 2: Rainy, (Worst) 3: Snowy. The main objective is to find the path that minimizes the total cost for a given origin-destination pair (n_o, n_d). If we assume availability of full information (crowd sourced) on the real-time traversability status of each sidewalk, then at time t, we know the complete traversable link status vector $H(t) = \{h_1(t), h_2(t), h_3(t), \ldots, h_{|E|}(t)\}$. The traversability status of each link can either be 1 (non-traversable) or 0 (traversable). Through the sequential decision making framework, we define the state $s \in S$ of the pedestrian at each decision stage k as $s = (n_k, t_k, H(t_k))$. At current location $n_k \neq n_d$, the pedestrian must make a decision on which adjacent node to travel. The information available at this stage includes the current time t_k and the traversable link vector $H(t_k)$. We balance the number of links to monitor with resulting projection accuracy by monitoring two links ahead of pedestrians current location. if E^1 and E^2 are the set of first and second successor links respectively from pedestrians current location, then state s_k is defined as $s_k = (n_k, t_k, H^{E^1 \cup E^2}(t_k))$, where $H^{E^1 \cup E^2}$ represent the traversability status of the set of first and second successor links from pedestrians current location. Our goal is to determine the optimal policy $\pi(s_k)$ showing which link pedestrian must select. Using the Q-learning method, the expected return starting at s, taking action a and following π is $Q^\pi(s, a)$. The optimal policy $\pi^*(s)$ for $s \in S$ is thus given by

$$\pi^*(s) = \underset{a}{\operatorname{argmax}} \quad Q^*(s, a) \tag{2}$$

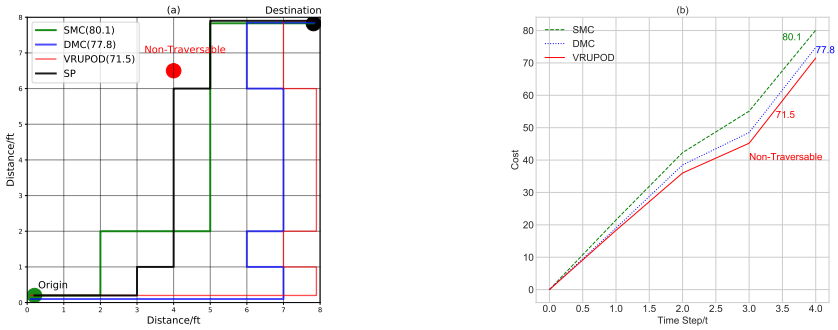
To illustrate the performance of our model, we present the results for data Boston sidewalk inventory. The cost of each edge is defined through Equation (1) for Static Minimum Cost (SMC): minimum cost path for a given O-D assuming the preferences of user is set at the beginning of trip and remains constant throughout the trip, Dynamic Minimum Cost (DMC): time-dependent minimum cost path through the adjustment of user preference at predefined periods or trip duration, the Vulnerable Road Users' Personalized Optimum Dynamic (VRUPOD): Our model using the Q-learning method and Shortest Path (SP): minimum distance from origin to destination. We carried out the case study on a simulated mid-size 8x8 network in a time frame [0-30] units. The predefined time-step for preference variation is set to 6 unit and characteristics remain static at $t \geq 30$. We assume that the longer the duration of travel, the more urgent pedestrian wishes to get to destination thus preference for shorter length increases with increasing duration of travel. For instance, a traveler who has covered about 70% of a trip would want to get the destination with minimal detours as possible because of tiredness and other consideration. We do this by varying the

weights assigned to length $W_l(t)$ at each predefined time-step to reflect the increasing importance in getting to destination. Figures 1 and 2 represents sample of results comparing the four models described above



(a) Path graph for four models (b) Cost graph for three models

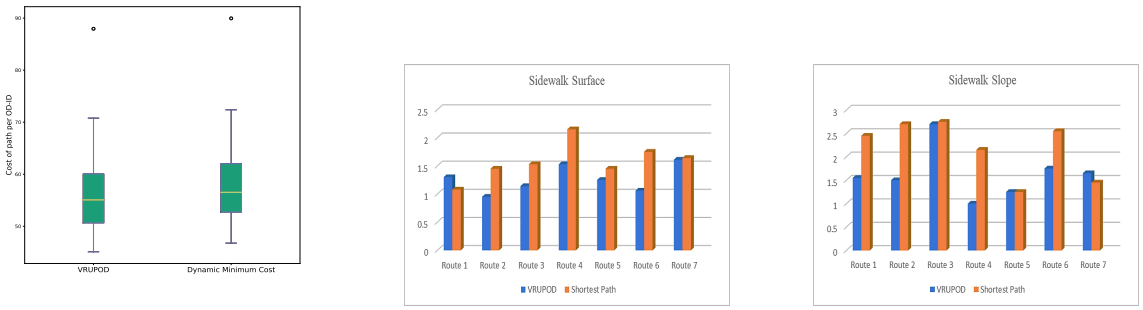
Figure 1 **Sample results of Path comparison of Four Models with Obstacle and Cost of Three Models by Time Step in rainy weather scenario**



(a) Path graph for four models (b) Cost graph for three models

Figure 2 **Sample results of Path comparison of Four Models with Obstacle and Cost of Three Models by Time Step in snowy weather scenario**

The path graph shows the various routes determined through the models. Cost evaluation of SMC, DMC and VRUPOD reveled the superiority of VRUPOD to the other models especially in the presence of multiple obstacles. In general, VRUPOD had a lower total cost when compared with SMC and DMC. In a Monte Carlo simulation to evaluate the robustness of our model, we randomly placed obstacles in the grid. The results shown in the box-plot (Figure (3a)) depicted a lower mean cost for VRUPOD when compared with DMC. We observed a similar trend for interquartile range for both VRUPOD and DMC with a slightly narrow range for VRUPOD than DMC. The whiskers for both models also followed a similar trend. In Figure (3b) we observe a general trend where VRUPOD found routes that minimized the total score for each route.



(a) score for surface type (b) score for slope (c) score for surface type

Figure 3 (a)Boxplot of Monte Carlo simulation results for path cost based on routing policies from VRUPOD and DMC method and (b,c) Score comparison for VRUPOD and shortest path routing algorithm

The average sidewalk surface type score and slope score in route recommended by VRUPOD were the low when compared to scores from SP. In this work, we presented how integrating a changing preference of vulnerable road users can be used to improve the overall navigation experience of people with disabilities. The method proposed incorporates real-time traversability information and updates the state action values through the cost formulation. Overall, VRUPOD routing outperformed SMC and DMC with VRUPOD also finding paths which minimized the scores of important parameters to the pedestrian when compared to SP. For future work we will apply VRUPOD to a large scale sidewalk network to further assess its robustness.

Acknowledgments

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