Crime-Avoiding Routing Navigation

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Abstract: ***Extensive prior work has provided methods for the optimization of routing based on the criteria of travel time and/or the cost of travel and/or the distance traveled. A typical method of routing involves building a graph comprised of street segments, assigning a normalized weighted value to each segment, and then applying the weighted-shorted path algorithm to the graph to find the best route. Some users desire that the routing suggestion include consideration pertaining to the reduction of risk of encountering violent crime. For example, a user desires a leisurely walk via a safe route from her hotel in an unknown city. Here, we present a method to quantify such user preferences and the risks of encountering crime and to augment the standard routing methods by assigning weights to safety considerations. The proposed method's advantages, in comparison to other crime-avoidance routing algorithms, include weighting crime types with respect to their potential detrimental value to the user, with temporal qualification and quantification of crime and its statistical aggregation at the geographic resolution down to a city block.***

Index Terms: Crime-avoidance, Crime classification, Crime data, Crime impact weighting, Multi-parametric routing, Navigation, Routing, Spatiotemporal analysis of crime

1. *Introduction*

Previous research [1-9] has developed methods for the optimization of routing based on the criteria of travel time and/or the cost of travel and/or the distance traveled.

Routing can be in various modalities, such as by car, on foot, by bicycle, via public transit, or by boat. A typical method of routing involves building a graph comprised of street segments, assigning a normalized weighted value to each segment, and then applying the weighted-shortest path algorithm to the graph in order to find the best route.

Routing can take into account preference parameters in addition to time and distance. For example, routing suggestions can include consideration pertaining to the reduction of the risk of encountering violent crime. For example, a user desires a leisurely walk via a safe route from her hotel in an unknown city. Here, we present a method to quantify such user preferences and the risks of encountering crime; we augment the standard routing methods by assigning added weights to said safety considerations.

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Galburn *et al.* [4] have utilized crime data to optimize the safety aspect of navigation within a city. Their case study involved urban crime data from Illinois and Pennsylvania. Their proposed risk model for the street network within a city facilitated estimating probabilities of criminal incidents that the traveler may encounter on any road segment. In their approach, the same importance is assigned to the path traversal time and the crime incident risk. Their method solves a dual-objective shortest-path problem.

Here, we present an improved method to co-optimize crime avoidance with other criteria. Advantages of the proposed method, in comparison to other crime-avoidance routing algorithms, include weighting crime types with respect to their potential detrimental value to the user, with temporal qualification and quantification of crime and its statistical aggregation at the geographic resolution down to a city block.

Figure 1 shows **traditional routing** optimizing the time and/or distance. In the example shown, the user wishes to walk from a house on the corner of 42nd Street and Sheridan Avenue in Miami Beach to the corner of Sheridan Avenue and Pine Tree Drive. The traditional routing algorithm offers the most direct path to the user's destination – walk northward along Sheridan Avenue.

In this paper, we present an improved method to co-optimize crime avoidance with other criteria. The proposed method's advantages, in comparison to Galburn [4] and the other crime-avoidance routing algorithms, include:

(1) weighting crime types with respect to their potential detrimental value to the user
(2) with temporal qualification
(3) quantification of crime and its statistical aggregation at the geographic resolution down to a city block and
(4) evaluation of the crime detriment to the user in each segment by considering the needs, exposure, and preferences of the user rather than merely considering the general crime incidence statistics.

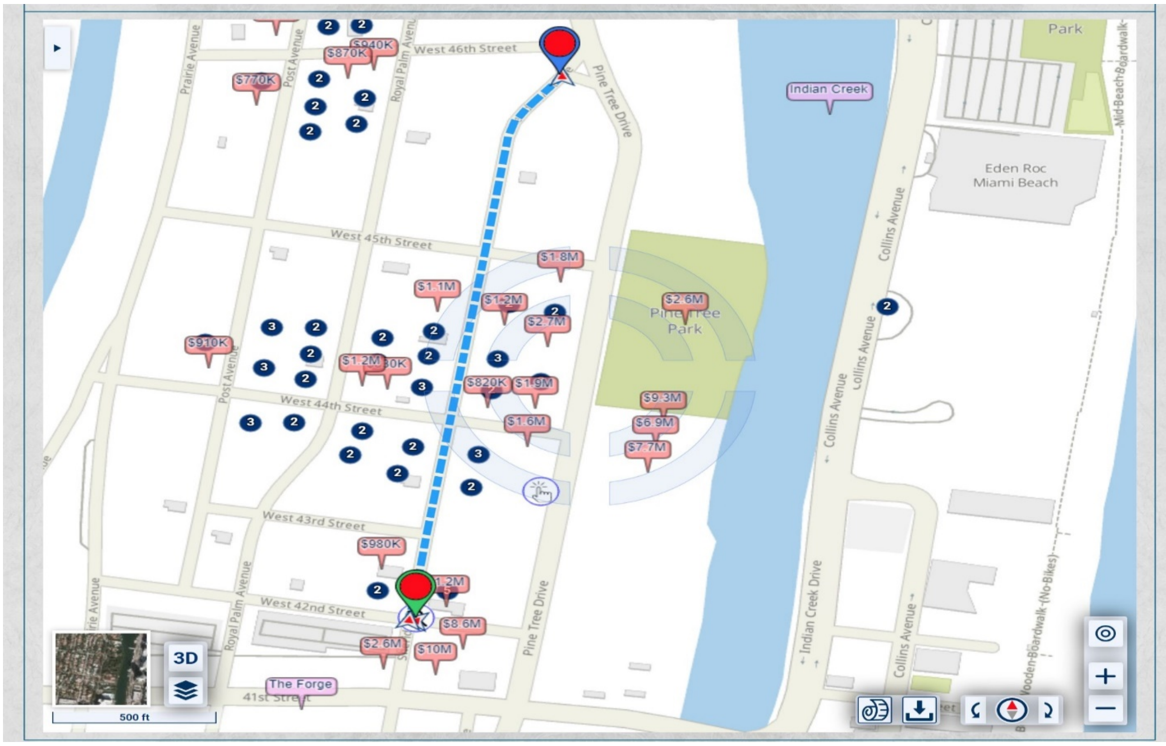


Figure 1: Traditional routing that optimizes time and/or distance

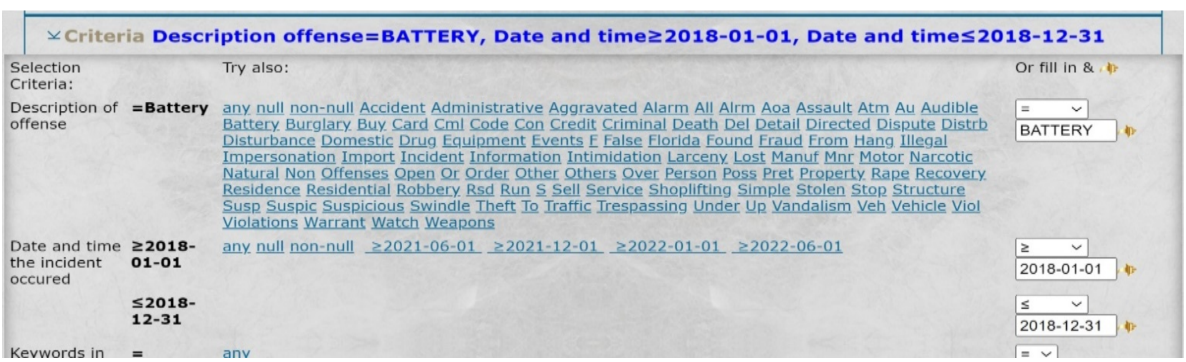
For example, violent crimes committed outdoors have a higher impact on the traveler than non-violent crimes or crimes committed indoors. Severe violence, such as homicide in the street, has the highest impact. Crimes without a direct unrelated victim, such as code violations or embezzlement, have no impact on travelers. The weights assigned to the different classes of crimes depend on the traveler's mode of transportation. For example, pickpockets have an impact on travelers in the walking mode but minimal impact on travelers by car. The weights assigned also depend on the demographics of the traveler. For example, non-statutory rape may be of high concern to a woman walking alone. For each type of traveler and travel modality, the present method provides default formulas for the evaluation of crime detriment in each segment.

Additionally, the user may modify the formula by assigning greater or lesser importance to various types of crimes

2. *METHODOLOGY*

In order to quantify crime risks for each street segment, we count police reports that occurred close to that segment during a set period of time, e.g., a particular year of reference, counting only violent and property crimes of the types that would directly affect the traveler (e.g., exclude domestic violence, exclude insider trading, exclude code violations, exclude statutory rape) and can further assign weights to various crime types based on the impact it may have in the traveler.

Figure 2 is an example of a **query to a crime database** for an area in mid-Miami Beach (Battery


Criteria Description offense=BATTERY, Date and time≥2018-01-01, Date and time≤2018-12-31

Selection Criteria:		Try also:	Or fill in &
Description of offense	=Battery	any null non-null Accident Administrative Aggravated Alarm All Alrm Aoa Assault Atm Au Audible Battery Burglary Buy Card Cml Code Con Credit Criminal Death Del Detail Directed Dispute Distrb Disturbance Domestic Drug Equipment Events F False Florida Found Fraud From Hang Illegal Impersonation Import Incident Information Intimidation Larceny Lost Manuf Mnr Motor Narcotic Natural Non Offenses Open Or Order Other Others Over Person Poss Pret Property Rape Recovery Residence Residential Robbery Rsd Run S Sell Service Shoplifting Simple Stolen Stop Structure Susp Suspic Suspicious Swindle Theft To Traffic Trespassing Under Up Vandalism Veh Vehicle Viol Violations Warrant Watch Weapons	= BATTERY
Date and time the incident occured	≥2018-01-01	any null non-null ≥2021-06-01 ≥2021-12-01 ≥2022-01-01 ≥2022-06-01	≥ 2018-01-01
	≤2018-12-31		≤ 2018-12-31
Keywords in	=	any	=

Figure 2: A sample query to a crime database

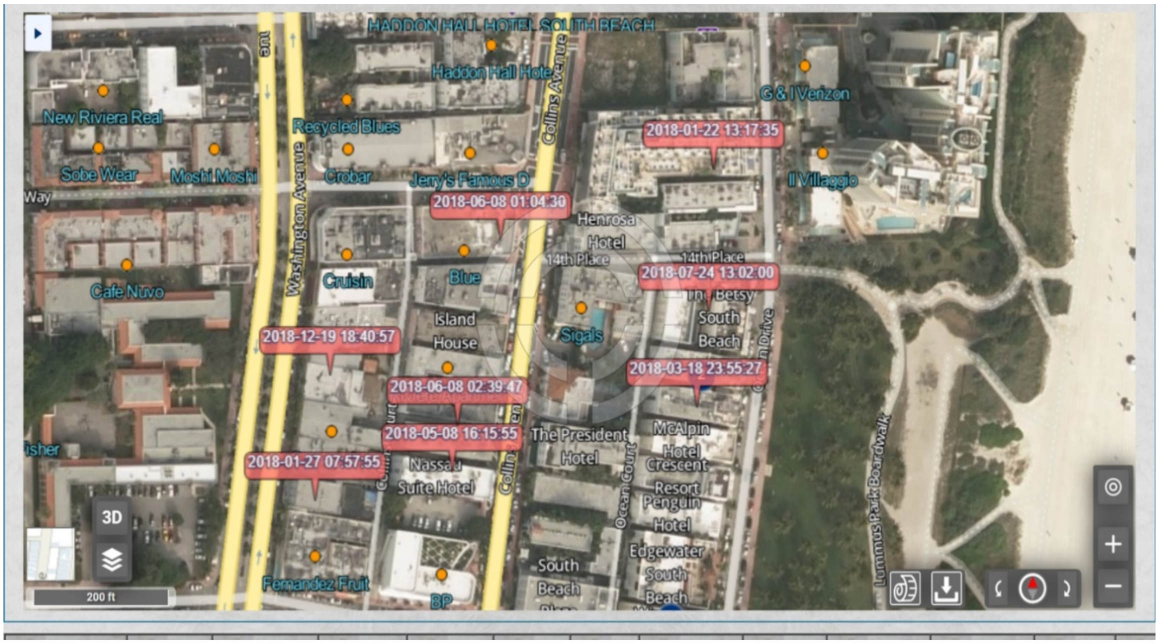


Figure 3: Map of query results (Battery committed in 2018 in Miami Beach)

offenses committed in 2018). The query, as formulated in Figure 2, searches the crime reports database for the incidents where the offense description contains the word "battery" and the occurrence date is between 2018-01-01 and 2018-12-31. The period for the aggregation of offense statistics is chosen arbitrarily, but it must be the same for all street segments being evaluated. The query formulation window also shows other offense types that appear in the field "Description of Offense" in the crime database. Among them, the relevant offenses, with varying weights depending on the travel modality, user demographics, and user-set preferences, include Homicide, Assault, Intimidation, Larceny, Rape, Robbery, and Vandalism.

The query in Figure 2 may result in a set of incidents (Battery in 2018), as shown on the **map**

Case number	Description of offense	Date and time the incident occured	Reported	Address where the incident occured	Police district	Clearance code description as reported by Officer	Business name involved in incident	Signal code description	Victim type description	Victim name(s)	Suspect name(s)	Arrestee name
MBc2018-00120592	Assault Or Battery OF LAW ENFOR-CEMENT OFFICERS, FIREF-IGHTERS, EMERGENCY MEDICAL CARE PROVIDERS, PUBLIC TRANSIT EMPLOYEES Or AGENTS, Or Other SPECIFIED OFFICERS; RECLA-SSIFI-CATION OF OFFENSES; MINIMUM SENTENCES	≤2018-12-19 18:40:57≥		1425 WASHI-NGTON AVE		APPROVED						
MBc2018-00054670	BATTERY-FELONY Battery	≤2018-05-18 06:48:59≥		600 ESPAN-OLA WAY		Closed						
MBc2018-00010991	BATTERY-FELONY Battery	≤2018-01-27 07:57:55≥		1409 WASHI-NGTON AVE		Closed No SOLVA-BILITY						
MBc2018-00061490	BATTERY-FELONY Battery	≤2018-06-08 02:39:47≥		1420 COLLINS AVE		1 - Closed N- A						

Figure 4: Tabular query output: Report of incidents (Battery committed in 2018 in Miami Beach)

of query results in Figure 3. The map in this example is centered on Collins Avenue in South Miami Beach. The map frame shows eight battery incidents reported in the area in 2018.

Figure 4 is a **tabular output** of the same sample query (Battery in 2018 in Miami Beach). Column 2 in the tabular output is the description of the offense (battery), and Column 3 is the date and time stamp. Column 5 is the street address where the offense occurred or other location information. The query also returns the coordinates of the incident, as computed from the address or other locational information. The coordinates are not shown explicitly in the output table in this figure.

Figure 5 specifies a query for **homicide incidents in 2018**, which should be considered with a higher detriment weight than battery. The Miami Beach area of the previous example did not have homicide reports during the sampling period (Year 2018).

Recentering the query in Northern Miami-Dade County, we see the **map of homicides in Figure 6** and their tabular display in Figure 7. The sample map area in North Miami-Dade County had 20 homicides in 2018 (12 of them are shown with dates in separate pink bubbles, and eight of them occurred in three clusters, shown on the map as blue cluster circles). As just an example of the assignment of weights to various types of crimes, depending on various factors relevant to the user, homicides might be assigned a detriment weight of 0.8, while batteries might be assigned a detriment weight of 0.3. As the tabular homicide query example of **Figure 7** shows, there are various subtypes of homicides, including murder, attempted murder, traffic homicide, etc. This may affect different weight assignments to the subtypes. For example, a detriment weight of 0.9 may be assigned for murder. Traffic homicide may be assigned the detriment weight of 0.5 in case the traveler is driving but only the detriment weight of 0.1 in case the traveler is walking. The first column in the table of Figure 7 implicitly shows the coordinates of the incidents (using directional arrows and distances with respect to the query's geographic reference point). It also shows that

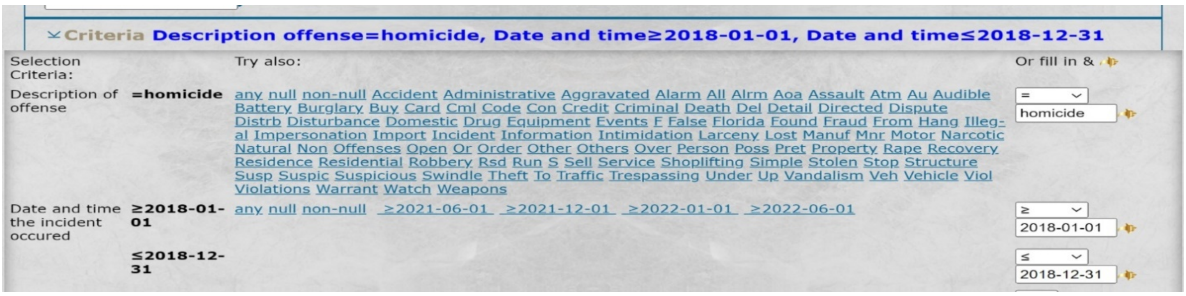


Figure 5: Homicide query (in 2018)

Figure 6: Homicide incidents in 2018, query results map centered in North Miami Dade County

while most addresses of the incidence were precisely geocoded (converted to coordinates), the first record's location was approximated with an error margin of 0.31 miles.

demonstrated by the query in **Figure 8**, whose results are mostly crimes that have no bearing on the prospective traveler, as shown in the map in **Figure 9** and the tabular output in **Figure 10**. In

links to locations & details	Case number	Description of offense	Date and time the incident occured	Reported	Address where the incident occured	Police district	Clearance code description as reported by Officer	Business name involved in incident	Signal code description	Victim type description	Victim name(
1: 0.2±0.31 miles	MGc20-18007-150	Information - Accident Traffic HOMICIDE	≤2018-04-21≥		18249 NW 17TH AVE NW 183RD ST	Zone 11					
2: 2107'	MGc20-18009-665	Information - Accident Traffic HOMICIDE	≤2018-05-28≥		1621 NW 179TH ST	Zone 11					
3: 2883'	MGc20-18016-121	HOMICIDE-MURDER	≤2018-09-03≥		1300 NW 180TH TER	Zone 11					
4: 2890'	MGc20-18020-205	HOMICIDE-MURDER	≤2018-11-02≥		17701 NW 15TH CT	Zone 11					
5: 3137'	MGc20-18008-225	HOMICIDE-ATTEMPTED MURDER	≤2018-05-07≥		17730 NW 13TH CT	Zone 11					
6: 3383'	MGc20-18013-358	HOMICIDE-MURDER	≤2018-07-23≥		18700 NW 23RD AVE	Zone 31					
7:	MGc20-	HOMICIDE-	≤2018-		2335	Zone					

Figure 8: Homicide incidents in 2018, query results table centered in North Miami Dade County

Criteria Date and time≥2018-01-01, Date and time≤2018-12-31

Selection Criteria:		Try also:	Or fill in &
Date and time the incident occured	≥2018-01-01	any null non-null ≥2021-06-01 ≥2021-12-01 ≥2022-01-01 ≥2022-06-01	≥ 2018-01-01
	≤2018-12-31		≤ 2018-12-31

Figure 7: Query not restricting crime types (Any "crime" in 2018)

The importance of querying for only specific types of crime (and weighting them) is

particular, Row 1 in Figure 10 describes the offense as a "prohibited act," likely a victimless

Figure 9: Map of the output of a query not restricting crime types (Any "crime" in 2018)

Case number	Description of offense	Date and time the incident occured	Reported	Address where the incident occured	Police district	Clearance code description as reported by Officer	Business name involved in incident	Signal code description	Victim type description	Victim name(s)	Suspect name(s)
MBc2018-00119260	PROHIBITED ACTS; PENALTIES	≤2018-12-15 01:13:19≥		200 30TH ST		Pending					
MBc2018-00116267	Larceny - Under $50.00 (+ ATT.)	≤2018-12-05 01:09:38≥		200 30TH ST		1 - Closed N- A					
MBc2018-00079230	Larceny - Under $50.00 (+ ATT.)	≤2018-08-01 10:52:39≥		200 30TH ST		Closed No SOLVA-BILITY					
MBc2018-00064680	FRAUD-ILLEG USE Credit CARDS	≤2018-06-18 10:56:58≥		2940 COLLINS AVE		Closed					
MBc2018-00115181	Larceny - $50 To $200	≤2018-12-01 08:53:53≥		2940 COLLINS AVE		Closed No SOLVA-BILITY					
MBc2018-00109397	MUNICIPAL ORDINANCE Viol	≤2018-11-10 12:32:44≥		2940 COLLINS AVE		Closed No SOLVA-BILITY					
MBc2018-00102292	FORCIBLE Rape COMMITTED	≤2018-10-18 14:46:55≥		2940 COLLINS AVE		APPROVED					
MBc2018-00118987	Assault AGG	≤2018-12-14 02:29:59≥		2940 COLLINS AVE		REVIEW					
MBc2018-00038646	Criminal MISCHIEF; PENALTIES; PENALTY FOR MINOR	≤2018-04-04 11:20:39≥		220 30TH ST		Closed					

Figure 10: Tabular output of a query that does not restrict crime types, including crimes irrelevant for the traveler, e.g., credit card fraud

crime. For some travelers, walking past such acts is displeasing, and a detriment weight of 0.1 might be assigned; for some other types of travelers, this might come with a detriment weight of 0. Row 4 in the same table describes the offense of credit card fraud. While there is apparently a victimized business, this offense has the detriment weight of 0 for the traveler, as the traveler would not be a potential victim in this case.

Figure 11 shows a route optimizing travel time via a traditional algorithm. The route traverses segments where relevant crimes have occurred during the sampling period. In this example, the traveler desires to walk from 340 31st Street in

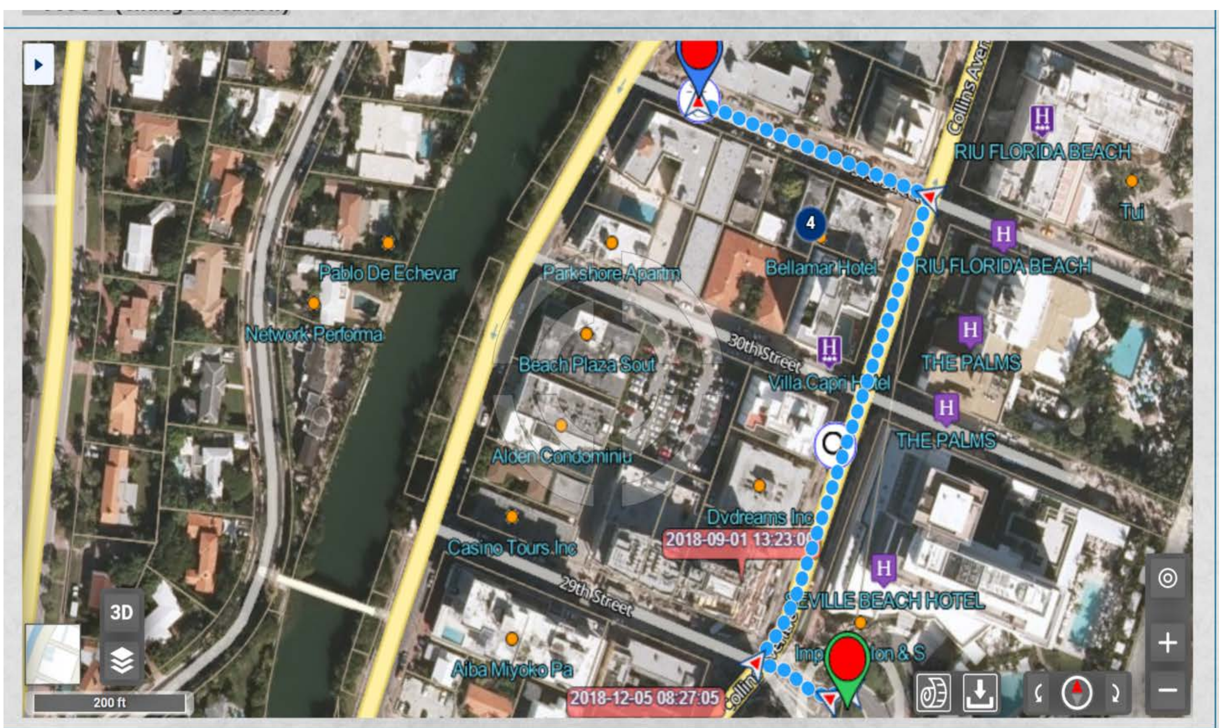


Figure 11:Time-optimized routing path, going through segments with higher crime potential

Figure 12: Routing co-optimizing time and crime avoidance

Miami Beach to 2700 Collins Avenue. The shortest route takes the traveler mostly through Collins Avenue, notwithstanding some danger to the traveler, since, historically, six relevant crimes occurred along this route in 2018: four crimes (clustered as a blue circle) on the traversed segment of 31st street and two crimes (shown as

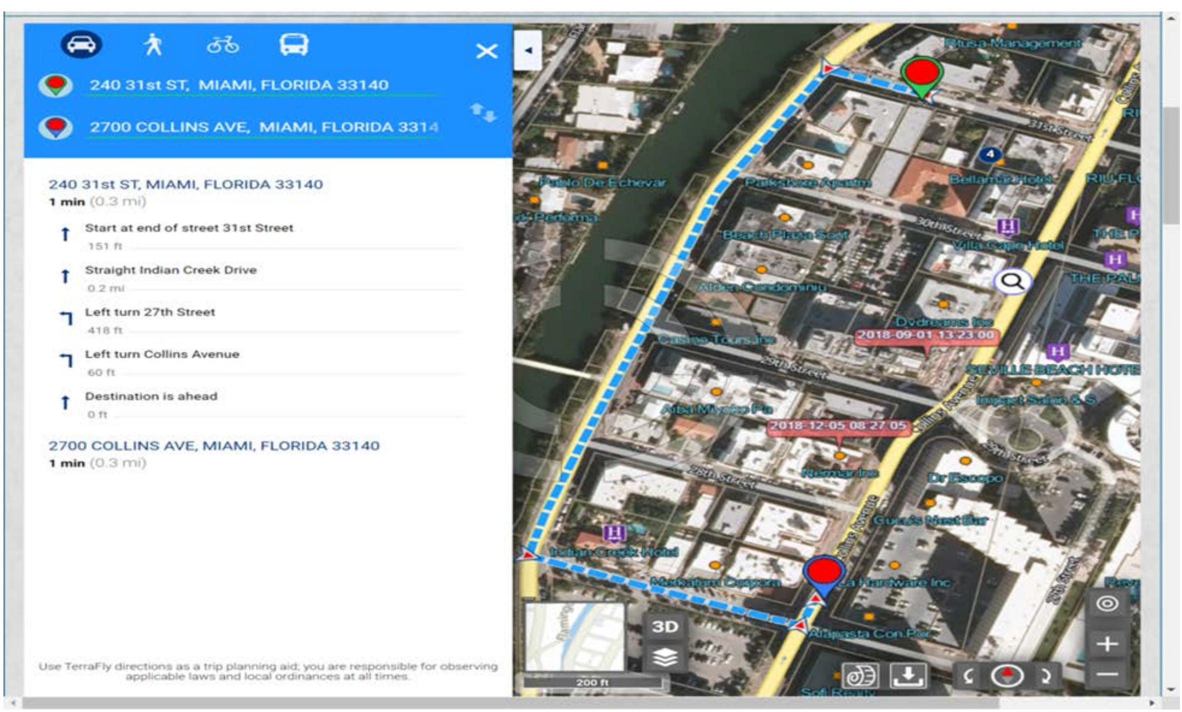


Figure 13: Time-optimized routing path, going through segments with higher crime potential, for various transportation modalities

pink bubbles) along the southern traversed segment of Collins Avenue.

By **co-optimizing the walk duration and crime encounter probability reduction**, we get a slightly different route, as shown in **Figure 12**. This safer route takes the traveler first southward along Indian Creek Drive, avoiding the crime-prone segments while only slightly increasing the travel time.

The routing may be different based on the **mode of walking or transportation**, as shown in **Figure 13.** The mode of transportation that the user desires affects the route choice both because of the traditional navigation issues (such as one-way streets and the varying maximal allowed and the actual current traffic speed in various segments), as well as due to the different detriment weights assigned to different types of crimes depending on the mode of transportation (e.g., pickpockets affect the pedestrian traveler, but not as much the

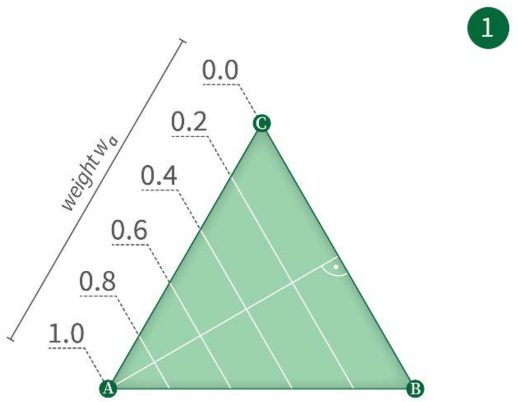


Figure 14: A weighting triangle with values of the importance of crime avoidance along one side of the triangle

driving traveler) The relative importance to the

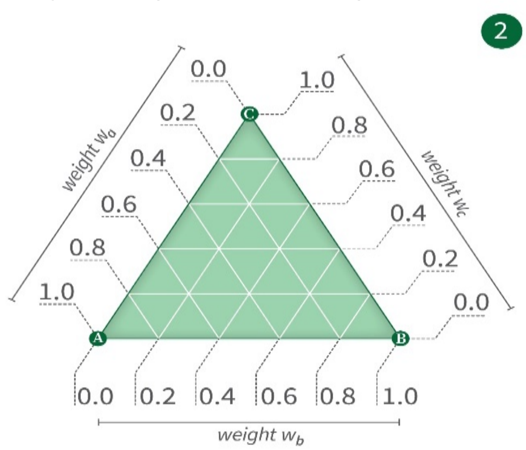


Figure 15: A weighting triangle with weighting values along all three sides, e.g., the weight of crime risk, weight of cost of travel, and weight of trip duration

user of time, cost of travel, and crime avoidance can be elicited from the user by utilizing our prior work's technology of the weight selection triangle (Figure 14): a touchable triangle allows the user to assign importance weights to three interrelated decision optimization objectives (Figure 15) using a single gesture (Figure 16) [10]. The sides of the triangle correspond to the weights that can be assigned to three different factors: crime risk, cost of travel, and duration of travel. By moving a finger or a pointer within the triangle, the user changes the relative weights of the three factors.

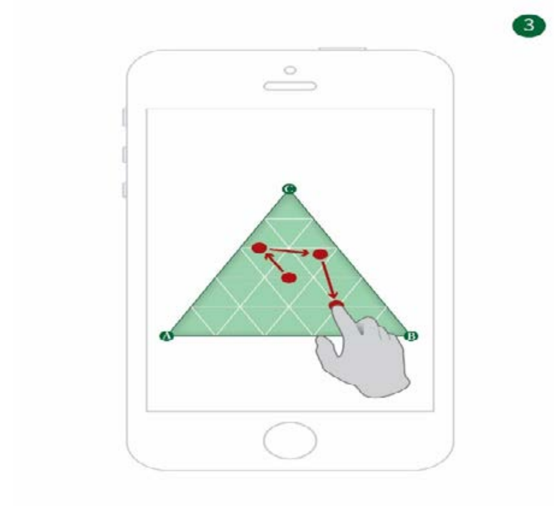


Figure 16: A smart device with the weighting triangle displayed thereon, showing a user selecting different weighting points, e.g., changing from a higher weight of crime avoidance to a lower weight, simultaneously with changing the weight of other factors.

We apply our previously published triangular selection method to the routing problem discussed in the present paper. Three objectives (A=time, B=cost of travel, and C=crime risk) are presented in a triangular fashion by the routing app on a touch screen. Figure 14 shows the underlying principle of the establishment of a single weight wA for Objective A; Figure 15 combines three objectives into a single triangle, allowing for the establishment of a tri-variable weight function (wA, wB, wC). By applying a finger gesture, the user moves an indicator freely inside the triangle (Figure 16). The position of the indicator establishes a tri-variable weight function, which, in further steps, is then used as input for the co-optimization algorithm. When the user is satisfied with the established weights, she indicates this, e.g., by pressing a touch screen button labeled "Go."

3. *THE ALGORITHM*

1. Build the **Generic Crime Model** of crime statistics per each street segment in the city:

a. Determine the sampling period, e.g., one historical year, for which a database of crimes reported is available, with addresses or other geolocation information of each crime.
b. For each segment and for each crime type (and subtype), compute the number of crimes of the type or subtype that occurred on the segment during the sampling period: *Quantity(segment,crime-type).*

2. Build a traditional model of navigation data, assigning to each segment and each mode of transportation the traversal time *Time(segment,mode)*, based on the typical travel time (for offline models) or the current actual traffic (for real-time models).
3. Build a traditional model of navigation data, assigning the monetary cost of travel to each segment and mode of transportation: *Dollars(segment,mode).*
4. Identify the traveler's demographics.
5. Identify the traveler's personal preferences.
6. Identify the traveler's mode of travel.
7. Identify the traveler's relative importance of crime avoidance versus the time and cost of travel: *Weight(factor)*, where *factor*=crime|time|cost.
8. From the traveler's demographics, personal preferences, and mode of travel, derive weight assignments to the different types and subtypes of crimes: *Weight(crime-type).*
9. From the Generic Crime Model, derive the **Traveler-specific Crime Model:**
    a. For each segment and crime type/subtype in the Generic Crime Model, compute Segment_Crime_Weight(segment, crime-type) = *Quantity(segment,crime-type) x Weight(crime-type).*
    The latter *Weight(crime-type*) has been derived above from the traveler's demographics, personal preferences, and mode of travel.
    b. Assign a cumulative crime risk cost to the segment as the sum of all the *Segment_Crime_Weight(segment, crime-type)* for all the disjoint crime-types or subtypes.
    c. Normalize the above per-segment cumulative crime risk as *Crime_risk(segment).*
10. Build a weighted graph (***Cost Graph***) of all the segments by assigning to each segment a cost factor as:
    Cost(segment) = *Crime_risk(segment) x wA + Time(segment) x wB + Dollars(segment) x wC*,
    where wA, wB, and Wc are the relative weights of crime risk, travel time, and travel monetary cost, as specified by the user or as defaulted based on the user's demographics and other general information.
11. Obtain and geolocate the user's starting point and destination.
12. Compute the user's suggested route using the conventional weighted graph traversal algorithm using the Cost Graph and the user's starting and destination points.

AVAILABILITY OF DATA AND MATERIALS

The data used in this work is available at http://terrafly.com. The geospatial data sets used in case studies to illustrate the method proposed herein can be provided by the corresponding author with appropriate arrangements.

COMPETING INTERESTS

The authors declare that they have no competing interests.

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