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Evacuation Traffic Prediction and Adaptive Control

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Abstract

The motivation for this proposed project derives from recent catastrophic events such as hurricane Harvey that has occurred in Texas. In the event of an evacuation before such catastrophe, city streets and highways experience traffic overflow that causes delay in evacuation and increases the likelihood of accidents. Evacuation related death reached 107 for Hurricane Rita, 3 for Hurricane Ike, and at least 15 for Hurricane Katrina as reported by Houston Chronicle. That said, an adaptive and resilient traffic-control needs to be developed considering such factors as location of evacuee's residence and location of shelter. In order to achieve adaptive traffic control during evacuation, traffic prediction is needed ahead of time. Given the map of a locality with houses and streets, traffic prediction can be automated. In this paper, authors present the creation of random map of residence, its characteristics, and identification of crowded intersections. The data with a neighborhood of 30 houses (with 5 roads and various sections) show diversity in residence in terms of distance and in terms of vehicle accumulation in road sections. Intersections identified (between houses and shelter) were 90 and corresponding traffic at various time points were calculated for each of them. This accumulation data and the direction of traffic would eventually facilitate adaptive traffic control.

1 Introduction

An increase in global warming, environmental degradation, and increased urbanization exposes a large number of people to the threat of natural disasters. The rate of disasters has increased from 50 to 400 percent in different regions within the last three decades and is anticipated to increase significantly in the next 50 years [1]. Managing large-scale evacuation during such a catastrophic situation is crucial. The fatalities has increased due to poor management of traffic during evacuation. Only in the USA, many people died in hurricane Rita, Hurricane Ike, and in Hurricane Katrina. All these deaths are related to evacuation as reported by print media. Authors in [2] has addressed adaptive traffic control framework but only for emergency vehicles. Researchers also proposed adaptive, preemptive control for electric tram but in non-disaster operations [3]. Authors in [4] also considered adaptive control in disaster evacuation based on real traffic obtained from sensors. Our work proactively predicts the traffic based on demographic information and attempts to identify clogged intersections for adaptive control. Researchers proposed deep learning to predict urban traffic behavior in [5]. However, the demographic input is not mentioned as we consider in our work. Similar work is presented in [6] and [7] with elaborate model development. In comparison, our work is based on model development and computational aspect of model implementation. Authors proposed prediction of real time traffic in [8]. In contrast, our approach is proactive based on existing demographic data. Vehicle to Infrastructure communication (V2I) is used in [9] to detect wrong way driving whereas we propose V2I for adaptive control of evacuation traffic.

Hence, the idea of developing an adaptive traffic control system naturally came especially after Hurricane Harvey that took place in Houston, Texas [10]. The purpose of this project is to automate the process of predicting traffic (from local demography) during disaster in intersections of road ahead of evacuation. This prediction will help infrastructure to adopt the best adaptive control during the emergency evacuation of traffic. This paper is organized as follows: methodology of traffic prediction and intersection identification is presented first, generated path array and vehicle accumulation data along with their characteristics are presented next, vehicles on each road section, extracted intersections and the detection of clogged ones are furnished after that. The paper concludes with recommendation of future work.

2 Prediction Methodology

Traffic prediction is based on area map of a locality. As no such digital map was readily available, we created such a map to start with, as described below. As a result, the work is divided into following steps:

1. Creating the map
2. Processing the map to predict the evacuation traffic based on source and destination
3. Identification of the critical intersections involved in evacuation

The above steps would facilitate creating the simulation program to implement adaptive traffic control.

Creating the Map

Initially, we have considered 30 houses that are randomly distributed over five roads. And each road consists of 5 sections. For the simplicity of the project, we have considered only one shelter at present. Also, the time associated with vehicles at each road (and section) ranges from one to five seconds. That is to say each vehicle takes one time unit to cross a road section. Each house consists of one vehicle. A sample illustration for road and section is shown below in Figure 1.

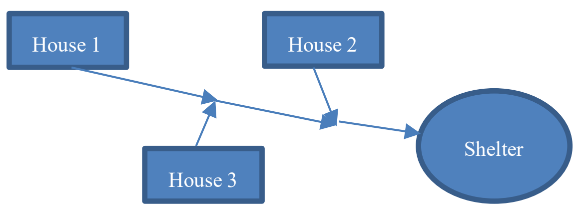

Figure 1. Diagram Representing Road and Sections between Houses and Shelter

The algorithmic steps for creating such a map is enlisted below.

1. Assign house ID from 1 to 30
2. For each house do:
    - Create five pair of values (road, section) between 0 and 5.
    - Set all (road, section) pairs to zero, if one of them is zero.
    - Correct discontinuities of (road, section) pairs.
    - Set the time for each (road, section) sequentially.

As a result of the above execution steps, a two dimensional array is created with 30 rows and 15 columns as shown in Table 1. It provides a detailed view of the route a vehicle (from each house) takes to reach the destination (shelter). Table 1 shows the actual route a vehicle takes during evacuation. For example, vehicle from house 1 takes road 2, section 3, then road 2, section 5, then road 1, section 3, and so on. A zero entry in the table indicates no road / section pair. Looking at the table closely it is evident that the generated map contains discontinuity. As an example, vehicle from house one takes road 2, section 3, then road 2, section 5, which indicates a jump from section 3 to section 5 of the same road (shown in red). Such discontinuities were identified and rectified such that a path contains sequential increase in sections on the same road.

Table 1: Path Array (partial) Showing Route Taken by Vehicles

Vehicle	Time unit	Road	Section
1	1	2	3
	2	2	**5**
	3	1	3
	4	5	1
	0	0	0
2	1	4	1
	2	1	1
	3	3	4
	4	1	2
	5	3	2

Algorithmic steps for correcting the discontinuities are as follows.

For each house do the following:

- Check two road / section pairs at a time
- If the road is the same and the section is not incremental, then make section incremental

Table 2 contains the corrected array. As seen in this table, vehicle from house one takes road 2, section 3, then road 2, section 2 (shown in green), which indicates a continuity from section 3 to section 2 of the same road. This corrected table was next analyzed to find its characteristics.

Table 2: Path Array (partial) after Removing Discontinuities

Vehicle	Time unit	Road	Section
1	1	2	3
	2	2	**2**
	3	1	3
	4	5	1
	0	0	0
2	1	4	1
	2	1	1
	3	3	4
	4	1	2
	5	3	2

Map Characteristics

Counting of the sections of road (a vehicle uses to reach from source house to shelter destination) was required to identify its characteristics. By analyzing the above table for all the houses, the number of road sections taken by a vehicle of each house can be calculated. A non-zero entry indicates a valid section whereas a zero entry indicates its absence. By following this principle, one can arrive at the following table. As seen in Table 3, vehicles traverse different number of road sections. It implies that the houses are not equidistant rather they are widely spread. Maximum number of vehicles (11) traverse 4 road sections whereas only one vehicle traverses only one section. This distribution indicates some sort of randomness of the generated path data array implying its proximity to a real map.

Table 3: Road Sections Traversed by Vehicles

# of Road Sections Traversed to Shelter	# of Vehicles
1	1
2	6
3	7
4	11
5	5

3 Results and Discussion

Predicting Traffic on each Section

Next step was to calculate the total number of vehicles at a specific section of road. For performing this analysis, algorithmic steps are as follows:

- Select a road section
- Select a time unit
- Check all the houses for a match of the road section and time unit
- If there is match, then increment counter
- Repeat the above steps for all the road sections

Following the above steps, one can conclude the following table with number of vehicles at each road section at different time units.

Table 4: Vehicle Accumulation Data at Road Sections

Time unit	Road	Section	Vehicles
1	1	1	2
2	1	1	3
3	1	1	2
4	1	1	1
5	1	1	0
1	1	2	0
2	1	2	1
3	1	2	1
4	1	2	0
5	1	2	2
1	1	3	1
2	1	3	1
3	1	3	2
4	1	3	0
5	1	3	0
1	1	4	1
2	1	4	1
3	1	4	0
4	1	4	0
5	1	4	1

As we look at the rows of Table 4, it is observed that (for a specific road section) the number of vehicles at different time points are different. For instance, starting with the top row (representing road 1, section 1) there are two vehicles at time point 1, three at time point 2, two at time point 3, one at time point 4, and none at time point 5. Such variation in the number of vehicles at other road sections is also evident from the complete table generated for the path array. Moreover, as we look at the rows, it is observed that (for a specific time point) the number of vehicles at different road sections are also different. For instance, in the fourth column, first row (representing time point 1) there are two vehicles in road 1, section 1. However, (in the fourth column, seventh row) no vehicles in road 1, section 2, and (in the fourth column, thirteenth row) one vehicle in road 1, section 3 and so on. Similar variation in the number of vehicles at other time points is also evident in the complete table generated for the path array. This variation clearly indicates randomness in vehicle data and is more representative of real life situation.

Identification of the Critical Intersections

From the vehicle accumulation data at road sections, road intersections and vehicle accumulation at each intersection needs to be identified. Intersections can be identified from the path array of Table 2 following these steps:

- For one house to shelter, every pair of non-zero road sections form an intersection
- Repeat the above for all 30 houses
- Check intersections of “one house to shelter” with others for overlap
    - If both Road/Sections are the same, then they are same intersection, remove one intersection from list
    - If both Road/Sections are different, then they are different intersections, keep intersection in list
    - If only one Road/Section is different (first sections are same, second sections are different or first sections are different, second sections are same), then it is shared intersection, keep intersection in list only once, add the new section

Executing this algorithm would generate a list of intersections with road sections forming each intersection. As an example, for path array of house 1, road two section 3 and road two, section 2 is an intersection as seen in Table 2. Similar conclusion can be drawn for road two, section 2 and road one, section 3 as well as road one, section 3 and road five, section 1. As such, following partial intersection list can be created from the corrected path data array of first two houses. The list would be extended by complete execution of the above algorithm.

Table 5: Derived Intersection List

Intersection	Road section pairs
I-1	Road two section 3 and road two, section 2
I-2	Road two, section 2 and road one, section 3
I-3	Road one, section 3 and road five, section 1
I-4	Road four, section 1 and road one, section 1
I-5	Road one, section 1 and road three, section 4
I-6	Road three, section 4 and road one, section 2
I-7	Road one, section 2 and road three, section 2

Predicting Traffic at each Intersection

The above list needs to be checked for overlaps, as mentioned in the algorithm. Thus, the generated list would be free from redundancies. However, it may contain intersections with more than two road sections. When such a list is produced with intersections and the road sections associated with it, the vehicles accumulated in the intersection can easily be calculated by summing the vehicles on each section at a specific time point. For example, considering I-1 of the above table, vehicles accumulated at time point 1 is sum of vehicles at road two section 3 and road two, section 2 i.e. (2+1) = 3, obtained from Table 4. In this way the vehicle accumulation at all the intersections can be computed for all time points. Such a table is created for all intersections and Table 6 depicts I-1, I-2, and I-7 showing vehicles at different time points.

It is evident from Table 6 that the intersections need to handle dynamic arrivals of vehicles. Total number of vehicles (at each intersection) over a certain time period can be calculated from this table. For example, the total number of vehicles at I-2 over the period of these five time points is (2+3+2+0+2) = 9. After such periodic calculation, the intersections with highest number of vehicles over that time period become the candidates for adaptive control.

Table 6: Vehicle Accumulation at Intersections

Intersections	Time unit	Vehicles
I-1	1	3
	2	2
	3	0
	4	0
	5	4
I-2	1	2
	2	3
	3	2
	4	0
	5	2
I-7	1	4
	2	4
	3	3
	4	3
	5	6

4 Conclusion

During disaster evacuation, appropriate traffic control measures should be taken. This paper explores the method of constructing the dynamic evacuation control of traffic during an emergency, such as a natural disaster. The model of house, road and sections are formed. Later, this model is implemented in the Visual Studio programming environment to determine the number of vehicles in each section of the road at a specific time point. From this data, traffic at various intersections are predicted and critical intersections are identified for adaptive control.

5 Further Research

In the next phase of the project, the number of shelters need to be increased, and the shortest distance between the source (house) and each shelter (destination) need to be determined. Besides this, we will identify the critical intersections and direction of traffic involved. Also, we will analyze solutions considering more parameters such as age and gender of residents. Also, estimation of evacuation time based on above prediction needs to be carried out.

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Conflict of Interest: none declared.

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