Traffic Accident Detection By Using Machine Learning Methods

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Abstract

There are lots of studies about preventing or detecting the car accidents. Most of them includes sensing objects which might cause accident or statistics about accidents. In this study, a system which detects happening accidents will be studied. The system will collect necessary information from neighbor vehicles and process that information using machine learning tools to detect possible accidents. Machine learning algorithms have shown success on distinguishing abnormal behaviors than normal behaviors. This study aims to analyze traffic behavior and consider vehicles which move different than current traffic behavior as a possible accident. Results showed that clustering algorithms can successfully detect accidents.

1.INTRODUCTION

Recent inter vehicular studies are acquiring commercial interest via the DSRC/WAVE standard in Vehicular Ad Hoc Networks (VANETs). Possible future services among vehicles are topic of many studies(Xu et al., 2004; Nandan et al., 2005; Lee and Gerla, 2010)

In VANETs, vehicles are able to communicate with each other in vehicle-to-vehicle (V2V) or with roadside network infrastructure in vehicle-to-Roadside Communication (V2R) manner. Some of the envisioned applications for vehicular networks are : vehicle collision warning, security distance warning, driver assistance, cooperative driving, cooperative cruise control,dissemination of road information, internet access, map location, automatic parking, driverless vehicles(Boukerche et al., 2008)

Most of applications need traffic speed and travel time measurements. These measurements can be used to help roadway users to decide which route to use or when to depart etc. Also These measurement can be saved to analyze traffic speed and travel time patterns for different time intervals. Currently local detectors at specific points along the road are used to measure the speed. New approach is to equip vehicles with communication and location devices to measure their speed and travel time. Some studies have shown that cellular networks can be used to identify vehicle's location using cellular phone base station communication records(Bar-Gera, 2007)

Safe navigation support has also become one of the main research topic with the help of DSRC/WAVE standardization(Jiang et al., 2006). For instance, collision or road condition warning messages can be forwarded to following vehicles. Beside DSRC/WAVE standards, 2/3G cellular networks can be used to enable message exchange among vehicles(Boukerche et al., 2008; Lee and Gerla, 2010)

In this study, we will use machine learning methods to analyze collected information from vehicles to detect forward collisions. Drivers will be alerted about collision and they will have time to take precaution to avoid piled-up collision.

2.BACKGROUND

Recently, automatic incident detection has attracted much attention in freeway control systems to reduce traffic delay, advance road safety, capacity and real time traffic control because when freeway and arterial incidents occur, they cause congestion and mobility loss, if they are not fixed immediately, they can cause second traffic accidents. Algorithms which is used to detect incidents include the pattern recognition techniques , time series(Angshuman, 2004), filtering, fuzzy set(Edmond Chin-Ping Chang and Kunhuang Huarng, 1993), and artificial neural network(Edmond Chin-Ping Chang, 1992) (Wang et al., 2007)

Unlike sensors, vehicles can be equipped with sensing devices with high processing power, high cost and weight like GPS, chemical spill detectors, video cameras, vibration sensors, acoustic detectors, etc.. since they are not usually restricted by energy and size constraints.

VANETs deployment scenario is different than traditional wireless sensor network deployment scenarios since vehicles expose limited mobility pattern due to street shapes, intersections, speed limitation, vehicle size. If vehicles are equipped with network cards, they can access wireless access networks like DSRC/WAVE, Cellular, Wifi, WiMAX, etc(Lee and Gerla, 2010)

2.1.Traffic Flow/ Incident Detection

Advances in ITS require more accurate traffic information and providing this information became a big challenge for the public institutions and private companies. The traditional traffic sensors that are used to measure current traffic conditions, like loop detectors, are ineffective to provide accurate information about traffic status on a road network.

Traffic related information from other sources , such as cameras, GPS, cell phone tracking, probe vehicles, are used to improve accuracy of the traditional measurement systems.

Traffic manegement control centers also keep these traffic related information for future use. Data fusion techniques can be used to combine offline traffic data and data from multiple sources in order to produce better understanding about road traffic state and future necessary road development(Faouzi et al., 2011)

Data fusion techniques that are used in traffic management include Dempster–Shafer inference, Bayesian inference, and voting logic. Most of these techniques combined probe vehicle data with traditional traffic data for incident detection. Neural network approach was also used to detect incidents from observed information(Faouzi et al., 2011)

2.2. Localization

Most of VANET application needs vehicles' current position. In order to compute the position of vehicles, Global Positioning System, Map Matching, Dead Reckoning, Cellular Localization, Image/Video Processing and Relative Distributed Ad Hoc Localization techniques has been studied. All of these techniques have advantages and disadvantages.

GPS signals may not be available in dense urban environments, tunnels, indoor parking lots, forests or underground environment or might be effected or blocked by obstacles, electronic interference. Also accuracy of GPS position can change from ±10 to 30 m. This accuracy array will occur at all nearby receivers. Map knowledge can be used to decrease the error at the position of vehicle that calculated by other techniques. Vehicles are supposed to follow roads, vehicle position can be match with road coordinates to estimate the location of vehicle(Krakiwsky et al., 1988; Jagadeesh et al., 2004)Dead reckoning technique compute vehicle location using its last known location based on direction, speed, time, etc when GPS signal is not available. Map knowledge can be combined to improve accuracy(Krakiwsky et al., 1988; King et al., 2005)Cellular localization techniques use cellular networks to estimate the position of the mobile phones(Han-Lee Song, 1994; Caffery and Stuber, 1998)Cellular localization is less accurate than GPS, localization error might change from 90m to 250m(Chen et al., 2006). Cellular localization results are not accurate enough for VANET applications but it can be useful when combined with other techniques. Local relative position maps are dynamic position maps which shows vehicles' relative position from other vehicles. Every vehicle estimates its distance from other vehicle and shares this information with nearby vehicles to construct local relative position map(Kukshya et al., n.d.; Boukerche et al., 2008)

3.METHODOLOGY

Machine learning methods showed great success at anomaly detection. In this study, we considered incidents in normal traffic flow as an anomaly. When accident happens, following cars will slow down or stop, and many cars will be affected from accident. When location data of vehicles are analyzed , it is seen that many cars are collected around accident location. Clustering algorithms can be used to group vehicles according to their speed and location in particular road segment. In accident case, algorithms will put vehicles which is affected by accident in one group , other vehicles in other group or groups.

In our simulations , it has been observed that number of group is increased by 1 at the time of accident and number of vehicles in the new group increased in the following seconds. It can be interpreted as an accident happened and following cars or cars around the accident are affected by the accident.

4.RESULTS AND DISCUSSION

In this study, Simulation of Urban Mobility, SUMO traffic simulator has been used to enable mobility of vehicles and collect position and sleep information. 100 vehicles has been used in 3000 m road segment. 5 different vehicle types has been used to imitate real life traffic.

Type	Length (m)	Acceleration (m/s2)	Deceleration (m/s2)	Max Speed (m/s)	Driving Perfectness
A	2	8	10	30	50%
B	4	2	10	30	50%
C	6	5	10	30	50%
D	8	4	10	30	50%
E	10	14	10	30	50%

Table 1 : Vehicle types and properties

SUMO traffic simulator is collision free traffic simulator. To simulate accident, cars are forced to make a stop in predefined position. Stops also can be considered important incident in a road segment. Vehicle itself or passengers who are leaving the vehicle might cause a problem. Identifying such incident and alerting coming vehicles will avoid possible accidents.

One car is forced to make a stop at 50 th second of the simulation. Deceleration value is chosen as 30 m/s2 to make stop instantaneously. DBSCAN (Sander et al., 1998) unsupervised clustering algorithm is used to create clusters. Every second, vehicle positions has been received from SUMO traffic simulator and fed to WEKA machine learning tool (Holmes et al., n.d.) Results of clustering structure as follows before and after the accident:

Simulation Time	Number of Cars in Road Segment	Normal Cluster	Anomaly Cluster
47	67	67	
48	68	68	
49	68	68	
50	68	67	1
51	71	68	3
52	71	68	3
53	74	70	4
54	76	72	4
55	76	72	4
56	77	73	4

Table 2: DBSCAN clustering results

When the car made a pre-scheduled stop at 50 th second of simulation, DBSCAN has been able to detect anomaly situation. Number of anomaly cluster increases after accident as expected because car stop or accident has blocked the road.

5.CONCLUSION

Automatic accident detection became very important topic in traffic management systems. Detection of accident will avoid future accidents and will help authorities to make road segment available for traffic again. In this study, we showed that traffic behavior can be analyzed using vehicle positions and speeds and abnormal activities on the road could be considered possible danger for the drivers who are close to incident area.

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