International Journal of u- and e- Service, Science and Technology
Vol.8, No.5 (2015), pp.13-22
http://dx.doi.org/10.14257/ijunesst.2015.8.5.02

Unreliable Road Network Traffic Detection and Prevention

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Abstract

Traffic in the road network acting a major role in the society. Everyday traffic is increased because of moving vehicles in the shortest path even though government handle traffic signal is based on the timing condition. Because of that travel time is increased from source to destination. The existing system handles the vehicular traffic using a two stage routing algorithms are time dependent landmark graph model is used to estimate travel time between two landmarks and the next stage is variance entropy based clustering model is used to estimate the distribution of travel time between two landmarks in different time slots. By using this algorithm, cannot estimate the speed pattern of the road segment and traffic has not been predicted and prohibited. To address these limitations a proposed system uses two ways are one is weight propagation model, the weights that captures the travel time and traffic can be extracted from the GPS (Global Positioning System) trajectory data collected from the network and another one ant colony optimization algorithm to estimate the optimal path apart from the traffic. Using this proposed algorithm the road network traffic has been detected and prevented.

Keywords: *Road Network, Routing Algorithm, Weight Propagation Model, Ant Colony Algorithm, Optimization.*

1. Introduction

In the fast-paced society of today, we are focused on arriving at our destination as quickly as possible. However, with this lifestyle, we are not always aware of all the dangerous conditions that are experienced while operating an automobile. Factors such as sudden vehicle maneuvers and hazardous road conditions, which often lead to accidents, are not always apparent to the person behind the wheel. In recent years, there has been tremendous growth in smart phones embedded with numerous sensors such as Evaluations, Global Positioning Systems (ROUTES), magnetometers, multiple microphones, and even cameras. The scope of sensor networks has expanded into many application domains such as intelligent transportation systems that can provide users with new functionalities previously unheard. Experimental automobiles in the past have included certain sensors to record data preceding test crashes. After that, analyzed real-time driving data to potentially recognize a future crash and actually prevent it.

With more than 10 million car accidents reported in the United States each year, car manufacturers have shifted their focus of a passive approach, *e.g.*, airbags, seat belts, and antilock brakes, to more active by adding features associated with Advanced Traffic Control Centre-Assistance Systems (ADAS), *e.g.*, lane departure warning system and collision avoidance systems. However, vehicles manufactured with these sensors are hard to find in lower priced economical vehicles as ADAS packages are not cheap add-ons. In addition, older vehicles might only have passive safety features since manufacturers only recently began to introduce an effective traffic control centre assist. Since sensors ultimately add onto the cost of a vehicle initially and cannot be upgraded, we target a mobile Smartphone as an alternative device for ADAS that can assist the traffic control centre and compliment any existing active safety features.

Given its accessibility and portability, the Smartphone can bring a traffic control centre assist to any vehicle without regard for on-vehicle communication system requirements. With this as our motivation, we envision a cheap and convenient mobile device that is able to analyze and advise the traffic control centre on sudden and harmful situations that arise from vehicle maneuvers and environmental factors. This type of traffic control centre assist is only meant to complement the traffic control centre but not to take full control of the vehicle. Providing constructive feedback to the traffic control centre is crucial in correcting bad driving behaviors. Recently, Ford and BMW have proposed ideas on this type of traffic control centre assist, where it can be integrated into their telemetric system, along with large number of other vehicles sensors. Given the sensing capability of smart phones, we use the internal Evaluation and ROUTE of the phone in place of the expensive hardware installed in vehicles to assist active features provided in newer ADAS vehicles. This paper is organized as follows; the both extreme driving behavior and hazardous road anomalies can be identified using a mobile phone rather than expensive motion equipment and can safety features to increase traffic control centre awareness. We conclude the essentially, the time that a traffic control centre traverses a route depends on the following three aspects: 1) The physical feature of a route, such as distance, capacity (lanes), and the number of traffic lights as well as direction turns; 2) The time-dependent traffic flow on the route; and 3) A user's driving behavior. Given the same route, cautious traffic control centers will likely drive relatively slower than those preferring driving very fast and forcefully. Also, users' driving behaviors usually vary in their progressing driving experiences.

2. Related Works

The fuel consumed by a vehicle is influenced by multiple factors [6, 7], such as *vehicle technology* (*e.g*., vehicle model and size, engine power, and type of fuel), *vehicle status* (*e.g*., mileage, age, and engine status), *vehicle operating conditions* (*e.g*., vehicle velocity and acceleration, power demands, and engine speed), *driving behavior* (*e.g*., aggressive driving), *air conditions* (*e.g*., atmospheric pressure, air humidity, and wind effects), *road conditions* (*e.g*., road grade and surface roughness), and *traffic conditions* (*e.g*., vehicle-to-vehicle and vehicle-to-control interactions). In general, different models consider different selections of these factors to compute fuel usage and GHG emissions. Models for estimating fuel consumption or GHG emissions have been developed over the past thirty years and can be classified macroscopic and microscopic scale models. Macroscopic models [17, 8, 9] account for the total fuel consumed during an extended time period (*e.g*., a day, a week, or a year) when traveling in an extended region (*e.g*., a city or a state) [18]. Macroscopic models are suitable for applications where coarse estimation of environmental impact is desired. However, macroscopic models are unable to accurately estimate the environmental impact of a particular road segment traveled by an individual vehicle or of a particular driving operation (*e.g*., braking hard), which are of interest in eco-routing and eco-driving. In contrast, microscopic models estimate the instantaneous fuel consumption or GHG emissions of individual vehicles at given time points (usually at seconds) using instantaneous velocities and accelerations. Some models utilize additional information, including vehicle status, vehicle operating conditions, and road conditions. Microscopic models are further classified into three categories [2].

Emission map models [20] provide lookups in velocity-acceleration matrices and return corresponding emission values. *Regression based models* [3] employ mathematical functions of second by- second velocities and accelerations of a vehicle to predict instantaneous fuel consumption or GHG emissions. They do not consider physical features of vehicles. *Load-based models* [19] are the most comprehensive microscopic models, and they consider a wide range of parameters, such as second-by-second velocities and accelerations, grades of road segments, air conditions, and engine maximum power, gear ratio, and engine power demands.

Microscopic models are often employed to evaluate the environmental impact of individual road segments on a spatial network and particular driving operations. The comprehensive load-based models generally offer the best estimates of fuel consumption. However, the required parameters are difficult to obtain for individual vehicles in a scalable manner. In contrast, regression-based models are fairly easy to apply because their input, *e.g.*, instantaneous velocities and accelerations, can be obtained directly from GPS trajectories.

3. Existing System

A smart driving direction system leveraging the intelligence of experienced traffic control centers. In this system, ROUTE-equipped taxis are employed as mobile sensors probing the traffic rhythm of a city and taxi rivers' intelligence in choosing driving directions in the physical world. We propose a time-dependent landmark graph to model the dynamic traffic pattern as well as the intelligence of experienced traffic control centre's so as to provide a user with the practically fastest route to a given destination at a given departure time. Then, a Variance-Entropy-Based Clustering approach is devised to estimate the distribution of travel time between two landmarks in different time slots. Based on this graph, we design a two-stage routing algorithm to compute the practically fastest and customized route for end users. We build our system based on a real-world trajectory data set generated by over 33,000 taxis in a period of three months, and evaluate the system by conducting both synthetic experiments and in-the-field evaluations.

On average, 50 percent of our routes are at least 20 percent faster than the competing approaches. A fast driving route saves not only the time of a traffic control centre but also energy consumption (as most gas is wasted in traffic jams). Therefore, this service is important for both end users and governments aiming to ease traffic problems and protect environment. Cannot guarantee there are sufficient taxis traversing on each road segment even if we have a large number of taxis. That is, we cannot accurately estimate the speed pattern of each road segment.

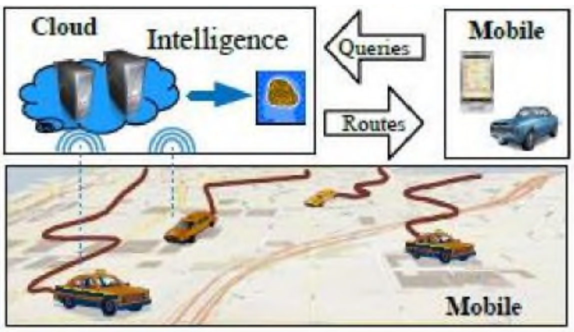

Figure 1. A Smart Driving Direction

System 3.1 Time-Dependent Landmark Graph Model

A landmark is one of the top-k road segments that are frequently traversed by taxi drivers according to the trajectory archive. We use landmark to model the taxi drivers' intelligence is that: 1) the notion of landmarks follows the natural thinking pattern of people, and can give users a more understandable and memorable presentation of driving directions beyond detailed descriptions. 2) The sparseness and low-sampling-rate of the taxi trajectories do not support the speed estimation for each road segment while we can estimate the traveling time between two landmarks. Meanwhile, the low-sampling-rate trajectories cannot over sufficient information for inferring the exact route traversed by a taxi. Thus, we can only use a road segment instead of their terminal points as a landmark. Here, we detect the top-k road segments as the landmarks instead of setting up a threshold, since a threshold will vary in the scale of taxi trajectories.

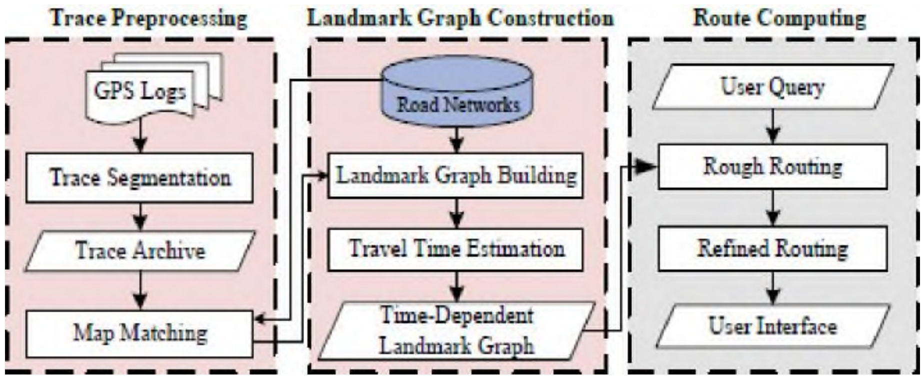

Figure 2. Time-Dependent Landmark Graph Model

3.2 Variance-Entropy-Based Clustering Approach

Variance-Entropy-Based Clustering approach is devised to estimate the distribution of travel time between two landmarks in different time slots. Based on this graph, we design a two-stage routing algorithm to compute the practically fastest and customized route for end users. We build our system based on a real-world trajectory data set generated by over 33,000 taxis in a period of three months, and evaluate the system by conducting both synthetic experiments and in-the-field evaluations. On average, 50 percent of our routes are at least 20 percent faster than the competing approaches. A fast driving route saves not only the time of a traffic control centre but also energy consumption (as most gas is wasted in traffic jams). Therefore, this service is important for both end users and governments aiming to ease traffic problems and protect environment.

4. Proposed System

In the existing system, a smart driving direction will have the problems are

- Traffic control centre assist is only meant to complement the traffic control centre but not to take full control of the vehicle. Providing constructive feedback to the traffic control centre is crucial in correcting bad driving behaviors.
- The traffic levels with an expert to wrong lane to driving in bad.
- Phone implementation showed acceptable results for drunken traffic control centre detection and is efficient in energy consumption.
- Low sampling- rate problem

So, that the proposed system using the weight propagation model to calculate the accurate weights of the network traffic with the help of GPS trajectory data for detection of the road network traffic and use the ant colony algorithm for routing the vehicle in the road network without traffic. Therefore the travelling cost and time will be consumed.

4.1 Weight Propagation Model

The goal of this task is to predict the cost for an arbitrary (possibly unknown) trajectory, based on a set of previous trajectory-cost pairs. The weight of an edge captures some cost associated with traversing the edge. It is a requirement to using a graph model for routing that all edges have weights. Weights that capture travel times and green house gas emissions can be extracted from GPS trajectory data collected from the network. GPS trajectory data typically needed to assign weights to all edges. In this equation $y(x)=\sum_{e \in x} Ce$ express the weights of all edges of the road segment. Where e is the link or edges of the road network, be the cost of the edges and y(x) is the total weight network to detect the traffic jams.

Propagation Penalty

One of the most important features of networks is the fact that an event at one location can propagate to the neighboring locations through the connecting links. Thus, if a link *e* has a significant deviation from its baseline state, then *e*'s neighboring links are expected to be influenced by that large deviation. This effect is easily understood by thinking about traffic jams.

Loss Function

It is clear that using the baseline costs for such links is not a good solution, since such static information does not reflect any changes in the actual traffic flow. Predicting the cost of a trajectory including any unseen links appears to be difficult. However, introducing another assumption that calls weight propagation makes it possible.

4.2 Ant Colony Optimization

Ant colony optimization is a part of the larger field of swarm intelligence in which scientists study the behavior patterns of bees, termites, ants and other social insects in order to simulate processes. The ability of insect swarms to thrive in nature and solve complex survival tasks appeals to scientists developing computer algorithms needed to solve similarly complex problems. Artificial intelligence algorithms such as ant colony optimization are applied to large combinatorial optimization problems and are used to create self-organizing methods for such problems.

Ant colony optimization is a meta-heuristic technique that uses artificial ants to find solutions to combinatorial optimization problems. ACO is based on the behavior of real ants and possesses enhanced abilities such as memory of past actions and knowledge about the distance to other locations. In nature, an individual ant is unable to communicate or effectively hunt for food, but as a group, ants possess the ability to solve complex problems and successfully find and collect food for their colony. Ants communicate using a chemical substance called pheromone.

As an ant travels, it deposits a constant amount of pheromone that other ants can follow. Each ant moves in a somewhat random fashion, but when an ant encounters a pheromone trail, it must decide whether to follow it. If it follows the trail, the ant's own pheromone reinforces the existing trail, and the increase in pheromone increases the probability of the next ant selecting the path. Therefore, the more ants that travel on a path, the more attractive the path becomes for subsequent ants. Additionally, an ant using a short route to a food source will return to the nest sooner and therefore, mark its path twice, before other ants return. This directly influences the selection probability for the next ant leaving the nest. Over time, as more ants are able to complete the shorter route, pheromone accumulates faster on shorter paths and longer paths are less reinforced. The evaporation of pheromone also makes less desirable routes more difficult to detect and further decreases their use. However, the continued random selection of paths by individual ants helps the colony discover alternate routes and insures successful navigation around obstacles that interrupt a route. Trail selection by ants is a pseudo-random proportional process and is a key element of the simulation algorithm of ant colony optimization

[10]. Detailed descriptions of ant behavior relating to ACO are found in [11, 12]. The use of ant colonies was first applied to the traveling salesman problem and the quadratic assignment problem [13] and has since been applied to other problems such as the space planning problem [14], the machine tool tardiness problem [15] and the multiple objective JIT sequencing problem [16].

5. System Design

This project consists of four modules are:

5.1 Road Simulate Mapping

The Evaluation readings, we recorded ROUTE coordinates at the time when road anomalies occurred. These anomalies are defined as a pothole, bump, uneven road, or rough road. We take the Evaluation value for a single ROUTE value and denote the Evaluation value as a segment of a particular area. In case of multiple Evaluation values, we use interpolation and assign that value to the particular segment. Each segment receives a corresponding value that designates the degree of the road: smooth road, pothole, bump, uneven road, or rough road. A dynamic classification method was used based on the vehicle speed obtained from the ROUTE. A color code technique is used and assigned to certain interpolated values for segments. A map of road conditions that was derived from the measurements taken around source and destination. From this, we can now visually see the conditions of the road before having to unwittingly experience them one lane of the road, in a single direction, which covers many of the heavily traveled roads around the city.

5.2 Evaluating Change Mode Traffic

The properly performing is a concern for many traffic control centers. Route problems can exist even while accelerating in high-speed traffic. Slipping in and out of route can frequently happen with older transmissions and can be a potential risk while driving on a highway. Using an evaluation roadmap, we found it possible to recognize gear shifts. For manual transmissions, sequentially shifting around 2500 rev/min is essential to sustain efficient fuel economy. Recognizing rate slippage in automatic transmissions can be an early warning of low transmission fluid, worn clutch discs, or a faulty shift solenoid, which are all essential components responsible for safely transporting a passenger.

5.3 Emergence and Traffic Control

The traffic control centre awareness about vehicle behavior is beneficial to everyone on the road. The way a vehicle is maneuvered on the road can influence how other traffic control centers react as they habitually follow previous movements to potentially avoid an unforeseen road hazard. The emergency and VIP are being traced to control the traffic centre and suddenly performed. The route to measure the traffic control centre’s direct control of the vehicle as they inform and apply the changes on signals. With the phone located on the center console, we recorded driving behaviors of acceleration and deceleration under safe and extreme conditions from all the vehicles listed in safe emergency exit.

5.4 Altering Lanes to Traffic Control

To detect lateral movements or lane changes performed by the road evaluation, we look at the Lane axis of the road. Using the previous phone orientation from the road analysis and density patterns, it is possible to recognize lateral movements created by an automobile and differentiate a left-lane change from a right-lane change. The formation of each maneuvers safe and sudden lane changes initiated by the driver. A left-lane change is portrayed by a decrease in x-axis, followed by an immediate increase, whereas a right-lane change is formed oppositely. These opposing patterns can be viewed.

6. Experimental Results

This project explains the traffic detection and prevention results are shown with status of the specific road segment, time travel difference from landmark to landmark and cost.

Figure 3. Road Network

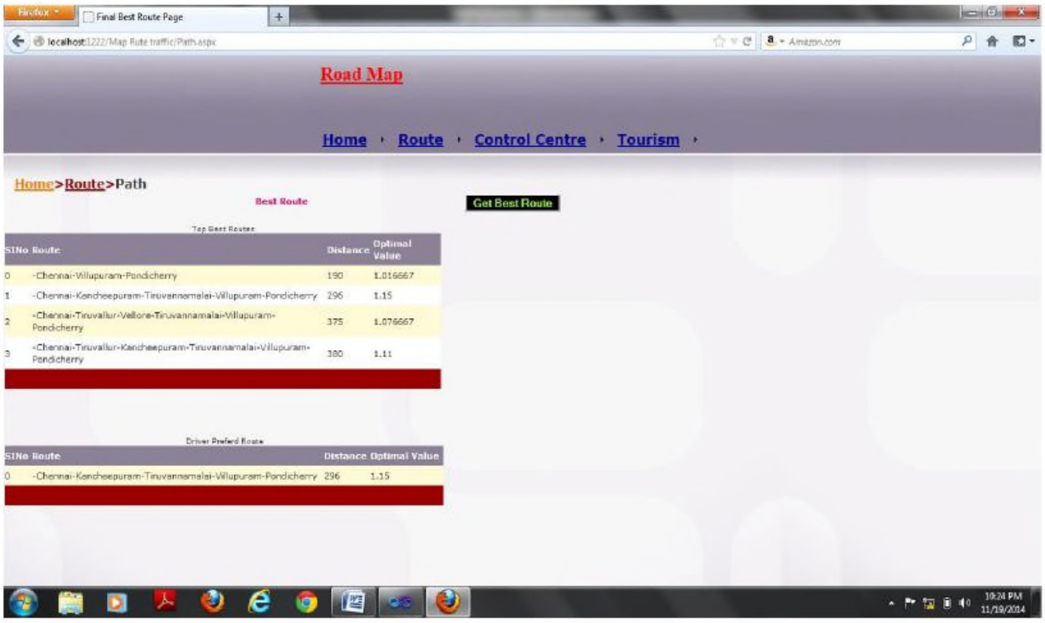

Figure 4. Calculate Optimal Value for Top Best Routes

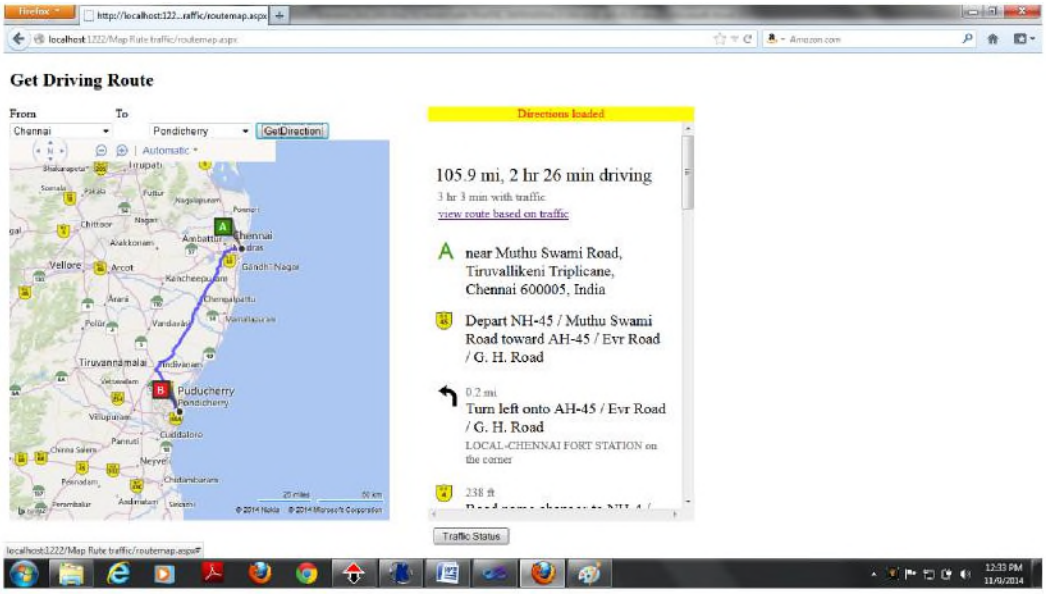

Figure 5. Route Estimation with Time and Cost

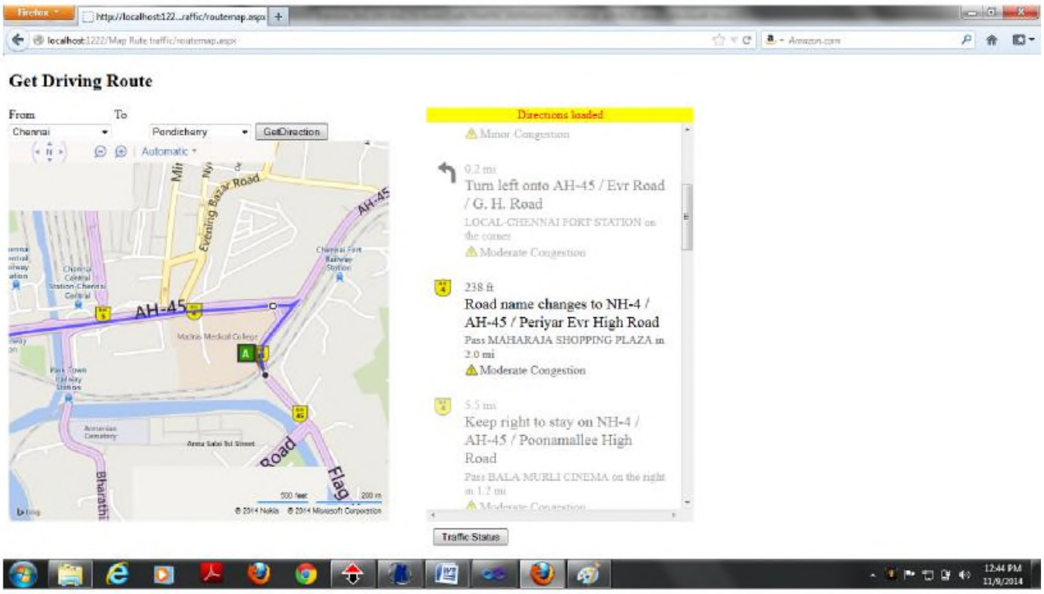

Figure 6. Traffic Detection and Prevention

8. Conclusion

This paper explains the vehicle routing and traffic detection by using weight propagation model. It determine the total weight of the road segment while calculating the travel time, cost and kinds of vehicle of each road segment. The total weight which is extracted from the GPS trajectory data from the mobile by this way the vehicular traffic has been detected. Then the traffic will be prevented by using Ant Colony Optimization algorithm for finding the another alternate optimal path. It will enhance the routing based on time as well as cost.

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