Travel time estimation using cooperative probes vehicles

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***Abstract*—This document presents an application using coopertive probes data based on real-world field testing to estimate travel time by applying adaptive Monte Carlo method and adaptive estimation from probes. The purpose is conducting the two methods to check which one gives better results in the context of database enrichment. Moreover the process should be run on the historical database and also it has to do real time computations. The innovative part of this work can be summed up in three sections. The first one is related to digital maping aspect, the second section is regarding the map-matching and GPS errors, and finally the adaptive estimation of travel time.**

***Index Terms*—Travel time, Cooperative probes, communication V2I, Monte Carlo method, Adaptive estimation method, Map-matching, Digital map.**

I. INTRODUCTION

A. Overview

Travel time plays a big role in giving information about the traffic status [7]. For this reason our paper is assessing two different methods that we adapted to our case and also to our new kind of database. The purpose is to look for the appropriate way to get the accurate travel time estimation which will be the mean by which we enrich the information of our historical database. We had the chance to apply our idea within the project PUMAS (Plateforme Urbaine de Mobilite Avancee et Soutenable / advanced mobility and sustainable urban platform).
The work was done within the PUMAS project which has as objective to inform about the traffic situation and to develop a platform for sustainable mobility to be evaluated in the region of Rouen, France. The innovative aspect of the project can be notice in the characteristics added to the digital map: we define a PUMAS point as the intersections between two different roads and a PUMAS section is the set of segments and nodes between two PUMAS points (Figure 1).

Moreover all our cooperative cars have this ability to communicate with the Pumas spots or the infrastructure via WIFI and if this latter is not available they can communicate the data collected via GPRS. This, way the information from the cooperative probes will always reach the server (Figure 1).

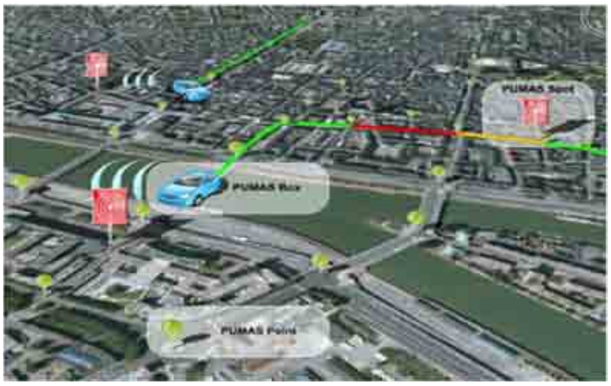

Fig. 1. The PUMAS Platform

B. Problem statement

Our objective is to estimate travel time in our historical database where the GPS data has a frequency of one minute between each successive input. This means that we have a lack of information between two successive GPS positions. The idea is to filter the data collected from our cooperative probes in order to correct all the errors related to the GPS and positioning on the digital map. Then, enhance the data with estimated travel time per road sections.

To fill the information gap, this experiment will give us reference data where the GPS information has a frequency of one second. We will use this information to simulate our historical data based on the collected data from cooperative probes on the field. Basically, we are going to take the GPS data with frequency of one second and create from it GPS data with a frequency of one minute. Next, we will correct all the biased data and then compute the estimated travel time using two different methods filter based on Monte Carlo method and adaptive estimation method from probes.

II. Data Collection

The experiment aims to gather data from the cooperative probes on the real-world field. Throughout the experiment we used three cooperative instrumented vehicles in order to acquire data from the fields in sufficient amounts to calibrate and analyse the behaviour of travel time estimator algorithms. Initially, we chose our itineraries by taking into consideration some constraints such as jams on small urban roads or on bridges that we might face so as to test the performance of the system in harsh circumstances.The expectations from this experiment on the field is to test the cooperative probes communication via the infrastructure to the server using the embedded system in the cars PUMAS Box (Figure 2). The PUMAS Box is a system that sends information to the server such as traffic jam if detected, GPS position, etc; and the data that we need for testing the travel time estimation algorithms.

Fig. 2. Embedded GPS System "PUMAS BOX"

The hazard of choosing the city of Rouen, France, give us a multitude of different kinds of urban area such as roadway, bridges in the city center, expressways, and small roads between buildings (Figure 3). Besides, the data acquisition in the field was based on different modalities such as traffic flow, traffic density, rush hours, etc.

Fig. 3. Itinerary Sample Reconstructed from the Collected Data

The following equipment was used:

TABLE I
EQUIPMENT

Equipment	Description
Three Citroen C3 LaRA	Intelligent vehicle of Ecole des Mines de Paris and IMARA team from INRIA, France.
WiFi and GPRS	Modes of transmission or communication between the cooperative vehicle and server
Pumas server	Server to retrieve data from PUMAS-BOX
Pumas Box	communicating with the server and send the data collected
GPS	fixed GPS embedded in the car
PC	embedded in the car with RT maps software
Coyote box	which we used in order to test our system and collect data in the real-world field.

The experiment outcome was more than 1400 km driven and almost 4GB of data was collected during three days.

III. System Architecture

The system outlined in (Figure 4), is designed to process the data received from the cooperative probes and create the digital map before computing the estimated travel time and architecture is as follow:

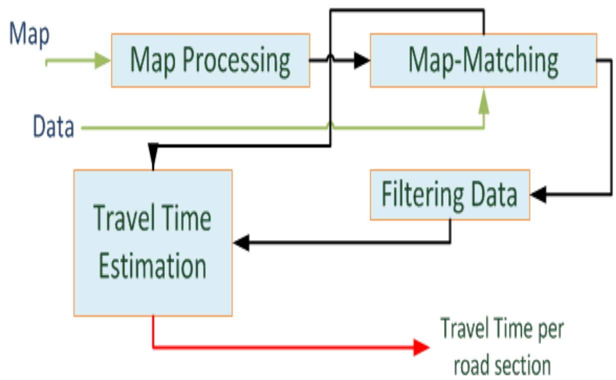

Fig. 4. Overview of the System Achitecture

A. Digital Map Characteristics

One of the innovative ideas of the project is the characteristics added to the digital map . We define a PUMAS point as the intersections between two different roads and a PUMAS section is the set of segments and nodes between two PUMAS points.

B. Map Matching Technique

The map matching was used to correct the GPS errors and match the GPS position on the appropriate road section [6]. The main process applied is defining the area of error around the GPS position [5] and applying an orthogonal projection [8]. In addition we added the notion of cap in order to enhance the map matching [5].

IV. Applied Methods to Estimate Travel Time

Our approach is to use two methods to estimate the travel time per road section. The first is the Monte Carlo method and the second one is an adaptive estimation method from probes.

A. Monte Carlo Method

The method that we applied to estimate travel time was an adaptive Sequential Monte Carlo filter [1],[2],[3]. The aim is to estimate travel time. The state evolution equation is as follows:

$$S_p = S_k + V_k * (t_p - t_k) + U \tag{1}$$

$$=> \quad t_p = \frac{S_p - U - S_k}{v_k} + t_k \tag{2}$$

Where S_p and S_k refers to the GPS coordinate of the PUMAS point and the first GPS data received, v_k is the speed of the car at the moment of receiving the GPS coordinate, t_p and t_k are respectively the time when the car was at the PUMAS point position and when we receive the GPS data, and finally U is a state noise that we add to the equation in order to refer to the imprecision of our parameters. In our case the parameters of our equation are known. Besides, we are not going to apply any model to the state equation; however, we will inject our data directly with the appropriate particle process for each known parameter in order to simulate the incertitude of our data. The particle that we apply is based on a normal distribution (Gaussian distribution) with a mean equal to the value of the parameter (S_k,v_k, U) and a total area under the normal curve is equal to 1. In our case, we will chose a probability density with a fixed standard deviation σ that will make evoluate the particles.Therefore equation (2) becomes:

$$t_p^{(i)} = \frac{S_p - U^{(i)} - S_k^{(i)}}{v_k^{(i)}} + t_k \tag{3}$$

Now we applied this formula to the first GPS data received and we called the estimated time of passage t_p forward (t_{pf}). Then we did the same thing for the second GPS data received after one minute and we called the time estimated of passage t_p backward (t_{pb}).

$$t_{pf}^{(i)} = \frac{S_p - U^{(i)} - S_k^{(i)}}{v_k^{(i)}} + t_k \tag{4}$$

$$t_{pb}^{(i)} = \frac{S_p - U^{(i)} - S_{k+1}^{(i)}}{v_{k+1}^{(i)}} + t_{k+1} \tag{5}$$

Moreover we attributed to each estimated t_{pf} and t_{pb} a weight using these equations:

$$W_1^{(i)} = \frac{t_{pf}^{(i)} - t_k}{t_{k+1} - t_k} \qquad W_2^{(i)} = \frac{t_{k+1} - t_{pb}^{(i)}}{t_{k+1} - t_k} \tag{6}$$

Where $W_1^{(i)}$ and $W_2^{(i)}$ are the weight of t_{pf} and t_{pb} respectively. Finally the estimation is computed as follow:

$$t_p = \frac{1}{2}\sum_{i=1}^{N}(W_1^{(i)} * t_{pf}^{(i)} + W_2^{(i)} * t_{pb}^{(i)}) \tag{7}$$

The algorithm will help us estimate at what time the vehicle passed by the PUMAS points tp_i and then we can compute the travel time per PUMAS sections Tp_j where j and i refers to the sections and PUMAS points respectively.

$$Tp_j = tp_{i+1} - tp_i \tag{8}$$

B. Adaptive Estimation from Probes

The methodology used to create this method is based on the background definition [4] of section travel time which is:

$$\bar{v} = \frac{\sum [min(x_{t+1}^n - x_{k+1}) - max(x_t^n - x_k)]}{\sum [min(t+1, t_{k+1}^n) - max(t, t_k^n)]} \tag{9}$$

Where N is the number of cars traversing the section during the time interval, x_t^n is the position of vehicle n at time t, x_k and x_{k+1} are respectively position of the upstream and downstream boundary, and finally t_{k+1}^n and t_k^n are respectively the times when vehicle n passes the downstream boundary and upstream boundary. If we apply this to our case, the equation will become:

$$T_p = \frac{1}{2}(\frac{x_{k+1} - x_k}{v_k} + \frac{x_{k+1} - x_k}{v_{k+1}}) \tag{10}$$

Where, T_p is the travel time between two GPS positions that we received with a frequency of one minute, x_k is the position of the first GPS data received, x_{k+1} is the position of the second GPS data received, v_k is the speed of the vehicle when we received the first GPS data and v_{k+1} is the speed of the vehicle when we received the second GPS data. In order to estimate Ip which is at what moment the car passed by the Pumas point, we will develop our equation as follow:

$$Ip = t_k + T_k \tag{11}$$

Where t_k is the time when we received the GPS data and T_k is the travel time between the position when we received the GPS data and the Pumas point that is between the two GPS data. If we take as hypothesis that the traffic inside the section is homogeneous, the development of the equation will lead us to the final expression shown below :

$$Ip = t_k + \frac{1}{2} * (\frac{x_p - x_k}{v_k} + \frac{x_p - x_k}{v_{k+1}}) \tag{12}$$

Where x_p is the Pumas point position. Then we will have the moment of passage by the Pumas points and we will conclude the Travel time per road section Tp_j by using the equation (6).

V. RESULTS

In order to evaluate the travel time estimation computed by the two methods we will apply the percentage difference of error based on our reference travel time collected from real world field work.

The graphs show that the Monte Carlo Method has a tendency to make less error compared to the adaptive estimation method (Figure 2). However, in order to be sure we will check the mean error of the two methods.

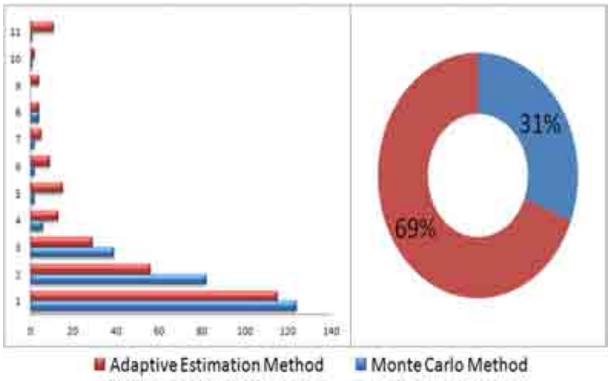

Fig. 5. To the left Histogram of the %Difference error and to the right the error accumulation made by the two methods (MCM 31% , AEM 69%)

- The mean error of the Monte Carlo Method (MCN): 7.07%
- The mean error of the Adaptive Estimation Method (AEM): 15.73%
- The standard deviation MCM: 13.66%
- The standard deviation AEM: 25.73%

After computing the mean it is clear that the Monte Carlo method produce less error. In addition we will run a t-test statistics to check if we can rely on this analysis using the mean error. We define our t-test hypothesis with α risks equal to 0.05:

- H_0: there is no significant difference between the percentage difference error in the two methods
- H_a: there is a significant difference between the percentage difference error in the two methods

After running the t-test with α risks equal to 0.05 we obtain the following results (Table II):

The t-statistic produced is less than the t-critical and the resulting p-value is less than the accepted α risk which leads us to reject the null hypothesis (Table 2). Therefore, there is a significant difference between the percentage difference error in the two methods. Therefore the t-test statistics confirm that Monte Carlo method produces a lower probabilty of making errors during the process of travel time estimation.

TABLE II
T-TEST RESULTS

	MMC	AEM
Mean	14.14	31.46
Variance	746.71	2650.04
Observations	263	263
Hypothesized Mean Difference	0	-
df	399	-
t Stat	-4.81	-
P(T¡=t) one-tail	1.02E-06	-
t Critical one-tail	1.64	-
P(T¡=t) two-tail	2.05E-06	-
t Critical two-tail	1.96	-

VI. CONCLUSION

The work presented a comparison of the performance of two methods to enrich a specific kind of database with travel time estimation per road section using the GPS information (one minute frequency) in the database. After the testing it is clear that the Monte Carlo produces less error during the experiment.

However when we check in the results locally we found that in some cases the adaptive method works better even if in general it is the MCM method which is better. That is why, we will create a classifier for the two methods in order to make our performance in estimating the travel time better.

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