Vehicular Congestion Modeling and Estimation for Advanced Traveler Information Systems

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Abstract— **It is widely accepted that the steady increase of urban vehicular congestion requires the implementation of adequate countermeasures. Intelligent Transportation Systems (ITSs) represent one of the possible solutions, as they strive to optimize the use of the available road network resources. Within this domain, the Advanced Travel Information Systems (ATISs) specifically address the vehicular congestion problem as they provide travelers, by means of a wireless channel, with updated road information. On receiving such information, travelers use their onboard Personal Navigation Devices (PNDs) to decide the best route to their destination. Clearly, ATISs become increasingly reliable the more they accurately identify the roads that are congested. We here propose a new model for detecting congestion that supports the accurate estimation and short-term forecasting of the state of a road to be used with ATISs. Such model can be generally applied to any type of street, as it does not require any a-priori knowledge, nor an estimate of any street parameter. We present the results of several experiments, performed on different urban roads, which confirm the efficacy of our proposal.**

Intelligent transportation systems, Advanced traveler information systems, Vehicular congestion detection and forecasting, mobility models.

I. INTRODUCTION

In the past few years, Advanced Traveler Information Systems (ATISs) have been highly referenced as of the most promising application of Intelligent Transportation Systems (ITSs). The purpose of ATIS policies is to provide all drivers with useful mobility information regarding their planned routes (e.g., travel time through multiple alternative paths) by having all cars sensing how rapidly they move (e.g., road traversal time) and utilizing a wireless channel to efficiently exchange such information between all vehicles and a centralized entity. Once the centralized entity has received a sufficient amount of information, such that an accurate picture of the levels of congestion can be built, vehicles' Personal Navigation Devices (PNDs) are fed with this information in order to compute the fastest route to destination [1]-[3].

The possible applications of ATISs are not limited to vehicular mobility, but also comprise pollution management, safety, entertainment and many more application fields (e.g., [4]-[8]). In many, if not all, of such, an accurate knowledge of both the current and the future traffic conditions could offer consistent advantages. For example, a pollution management application could use such information to divert traffic flows when the pollution levels due to carbon dioxide rise above a given threshold, and a safety application could alert transportation authorities when congestion abruptly builds up on a given street, thus indicating an accident might have occurred.

It is, however, very difficult to track the trend of traffic mobility in urban areas, as streets display variable traffic patterns and can easily become congested. In fact, even if a fine-grained network of vehicles were used to sense traffic, this should still need the support of an ATIS that efficiently determines and forecasts its mobility rate, distinguishing the streets that are congested from those that are not.

Clearly, the first step in building such type of ATIS consists of providing it with an operative definition of what traffic congestion is for any given street. Although many definitions of vehicular congestion exist, we were unable to find one that returned unambiguous results and was contemporarily independent of any assumed street parameter. We therefore devised a brand new one, by drawing our inspiration from the packet pair schemes that estimate the capacity of an Internet connection [9]. Our definition derives from the simple consideration that if a first car travels across a street when it is congested, a second car will probably experience the same congestion granted that it entered the street not too far away in time from the first car. Such phenomenon is due to the inertia of vehicular queues, which causes a street to be seen as congested also by those vehicles that later enter it (say within a time span *S*). This consideration allows us to define congestion as a state that *lasts for at least S units of time* and during which travel times or delays exceed the time T^* normally incurred under light or free-flow travel conditions.

The scope of this paper is to present a novel algorithm to be used with ATISs, which is able to detect vehicular congestion situations, as well as its duration, based on the congestion definition mentioned before. The novelty of our algorithm is that it works for any type of road without any prior knowledge, while it is able to perform short-term congestion forecasting by simply analyzing the information gathered by probing vehicles.

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We validated our approach carrying out over 450 miles of on the road experiments, performed in two very different cities, Los Angeles (CA), and Pisa (Italy), during 2008 and 2009.

The rest of our paper is organized as follows. In Section II we provide a succinct review of the schemes that fall closest to distinguishing congested from non-congested roads. In Section III we sketch the model that led to the design of our algorithm and show how this can be integrated within an ATIS in Section IV. The experimental assessment with empirical results is presented in Section V. We finally conclude with Section VI.

II. Related Work

Although a wealth of work in the area of congestion detection and forecasting algorithms exist, for the sake of brevity, we here only describe two approaches that most easily can be integrated with an ATIS [10]-[16].

The first one, termed Surface Street Traffic Estimation, was proposed to identify congestion on streets that ended on traffic-light controlled junctions [14]. In brief, based on this approach vehicles are considered to experience congestion if they incur in one of the two following situations that may slow down their flow. They could waste time by either moving following a *stop and go* pattern, or by waiting in queue for at least one full red light cycle. This approach is recognized to fall short as it lacks of any forecasting power and it is only defined for streets that end at signalized intersections, thus leaving its extension to more general cases unsolved.

The second approach is based on the Highway Capacity Manual (HCM) delay formula for signalized intersections [15]. This formula assesses the average delay d_{HCM} experienced by a vehicle traversing a street as a function of: the length of the street, its speed limit, its capacity (which depends upon its number of lanes and on the length of its traffic light phases) and the average amount of vehicles entering it within a given time. The d_{HCM} value, computed when the ingress traffic volume matches its capacity, returns useful information to distinguish when a given section of road is congested or not. The main limit of such approach is given by the fact that it relies upon statically chosen road parameters, hence jeopardizing its adaptability to new road settings.

In the following, we will show a new approach able to detect and forecast congestion, while avoiding any of the pitfalls mentioned here.

III. Congestion Detection and Forecasting: A Summary

Based on the traffic congestion definition provided in Section I, it is easy to compute the congestion threshold T^* as well as the time S for which congestion or non-congestion persists on any given road R. This mechanism is as follows. We regard a road R as congested if it is possible to find a value of T^* for which, when a vehicle requires more than T^* units of time to traverse it, the majority of subsequent cars (e.g., 80%) that later enter R (say within a time span S) still need at least T^* units of time to exit it. If, instead, the percentage of subsequent cars that experienced a traversal time above T^* units of time were low (e.g., much below 80%), this would mean that R is leaving a state of congestion. Similarly, R is non-congested when, if a vehicle requires less than T^* units of time to traverse it, the majority of subsequent vehicles that flow through (e.g., 80%) it still require less than that time. Alternatively, in the event that the percentage of subsequent vehicles that experienced a traversal time below T^* were low (e.g., much below 80%), this would mean that R is moving into a congested state. The 80% value has been inspired from literature [17]. Obviously, different values can be taken depending on the specific road under consideration.

It is now straightforward to map the above ideas into a more formal modeling setting from which we will derive our congestion detection and short-term forecasting algorithm.

We will provide in the following formal tools (Definitions 3.1, 3.2, 3.3 and 3.4) with which we will be able to count and compare: a) the number of pairs of vehicles which suffer of high congestion ($HC(T_1^*)$) versus the number of pairs of vehicles which are leaving a congested situation ($N1(T_1^*)$), and b) the number of pairs of vehicles which do not suffer of congestion ($NC(T_2^*)$) versus the number of pairs of vehicles which are entering in a congestion state ($N2(T_2^*)$).

Definition 3.1 (High Congestion Set). Consider a group P of vehicles entering a street R, with the first vehicle of the group entering R at time t_0 and the last one entering R no later than time $t_0 + S$. $HC(T_1^*)$ is defined as the set of all the pairs of vehicles, (i, j), in P for which both their traversal times, say T_i^* and T_j^*, exceed the congestion threshold T_1^*. We also define as $N1(T_1^*)$ the set of all the pairs of vehicles, say (h, k), in P for which the traversal time T_h^* of only the first vehicle h exceeds T_1^*.

Definition 3.2 (Low Congestion Set). Take the same group of cars P entering R within a time span of the same length as before. $NC(T_2^*)$ is defined to be the set of all the pairs of cars, say (i, j), in P for which both their traversal times, say T_i^* and T_j^*, are below the congestion threshold T_2^*. Consequently, $N2(T_2^*)$ is the set of all the pairs of cars, say (h, k), in P for which the traversal time T_h^* of only the first vehicle h is below T_2^*.

Definition 3.3 (High Congestion State). Let $I_{HC(T_1^*)} : (P \times P) \rightarrow \{0, 1\}$ be defined as:

$$I_{HC(T_1^*)}((i,j)) = \begin{cases} 1 & (i,j) \in HC(T_1^*) \\ 0 & (i,j) \notin HC(T_1^*). \end{cases}$$

Let $I_{N1(T_1^*)} : (P \times P) \rightarrow \{0, 1\}$ be defined as:

$$I_{N1(T_1^*)}((i,j)) = \begin{cases} 1 & (i,j) \in N1(T_1^*) \\ 0 & (i,j) \notin N1(T_1^*). \end{cases}$$

Similarly, for non congested states:

Definition 3.4 (No Congestion State). Let $I_{NC(T_2^*)} : (P \times P) \rightarrow \{0, 1\}$ be defined as:

$$I_{NC(T_2^*)}((i, j)) = \begin{cases} 1 & (i, j) \in NC(T_2^*) \\ 0 & (i, j) \notin NC(T_2^*). \end{cases}$$

Let $I_{N2(T_2^*)} : (P \times P) \rightarrow \{0, 1\}$ be defined as:

$$I_{N2(T_2^*)}((i, j)) = \begin{cases} 1 & (i, j) \in N2(T_2^*) \\ 0 & (i, j) \notin N2(T_2^*). \end{cases}$$

Following our ideas, we now provide the two following Propositions 3.1 and 3.2, aimed at verifying if the percentage of cars experiencing congestion or not satisfies the threshold of 80%.

Proposition 3.1: (Congestion). A given street *R* is congested for a period *S* if the following holds:

$$\frac{\sum_{(i,j) \in P \times P} I_{HC(T_1^*)}(i, j)}{\sum_{(i,j) \in P \times P} I_{HC(T_1^*)}(i, j) + \sum_{(i,j) \in P \times P} I_{N1(T_1^*)}(i, j)} \times 100 \geq 80\%.$$

The same can be drawn for a non-congested state, as follows:

Proposition 3.2: (No Congestion). A given road segment *R* is not congested during a period *S* if the following holds:

$$\frac{\sum_{(i,j) \in P \times P} I_{NC(T_2^*)}(i, j)}{\sum_{(i,j) \in P \times P} I_{NC(T_2^*)}(i, j) + \sum_{(i,j) \in P \times P} I_{N2(T_2^*)}(i, j)} \times 100 \geq 80\%.$$

An efficient way to solve our problem is to first determine the values of T_1^* and T_2^*. This step is performed in the following searching for the pair (T_1^*, T_2^*) which maximizes the size of the $HC(T_1^*)$ and $NC(T_2^*)$ sets (congested and non-congested states, respectively) and, contemporarily, minimizes the size of the $N1(T_1^*)$ and $N2(T_2^*)$ sets (noisy states).

Proposition 3.3: Given a set of traversal time pairs on *R* sampled during both congested and non-congested states, a congestion threshold T_1^* and a non-congestion threshold T_2^* can be obtained as:

$$\begin{aligned} (T_1^*, T_2^*) = (T_1, T_2) \quad s.t. \\ \{\max_{T_1, T_2} \sum_{(i,j) \in P \times P} & I_{HC(T_1)}(i, j) + \\ & + I_{NC(T_2)}(i, j) + \\ & - I_{N1(T_1)}(i, j) + \\ & - I_{N2(T_2)}(i, j)\}. \end{aligned}$$

Once T_1^* and T_2^* have been obtained, they are to be checked to verify that the inequalities expressed in Propositions 3.1 and 3.2 are satisfied. This ends our model.

IV. A Novel Congestion Detection Algorithm for ATIS

In Table I we now explain how the model above can be implemented and deployed within an ATIS.

Specifically, the centralized entity within the ATIS observes and gathers traversal time data concerning a given road *R* as returned by a set of probing vehicles. On receiving traversal time samples from vehicles, this entity keeps adding them to an internal data structure (line 2, Table I) until a sufficient number of observations have been collected and that road has been observed for half a day (lines 3 and 4). At the end of this initial process, the entity quits gathering information about the street (line 5) and builds its picture of the congestion states characterizing that given street, using the `CTDF()` function (line 6). The `CTDF()` function amounts to the implementation of Proposition 3.3, as explained later. If any time later, be it one hour or one month, a vehicle traverses that given street exceeding the computed congestion threshold T_1^*, the entity can exploit this information to, for example, send a congestion alert message to all those vehicles that are approaching its area (line 11).

TABLE I. ATIS ALGORITHM

Input: Traversal time *T* of a vehicle that traverses a given road *R*.

Output: Road *R* congestion information.

1. **if** collectingData == **true then**
2. collectedTraversalTimes`.Add(`T`);`
3. **if** R.observationTime > 12 h **and**
4. collectedTraversalTimes.Length `> 100` **then**
5. collectingData = **false;**
6. $(S, T_1^*, T_2^*) \leftarrow$ `CTDF(`collectedTraversalTimes`);`
7. **end**
8. **end**
9. **else**
10. **if** $T > T^*$
11. `alertCongestion(`*R*`);`
12. **end**
13. **end**

Now, it is the turn to describe how the `CTDF()` function works (Table II). As already said, it implements the mechanism described in Proposition 3.3. Namely, it seeks for the values T_1^* and T_2^* that both maximize the two sets of high congestion ($HC(T_1^*)$) and no congestion ($NC(T_2^*)$) and minimizes the remaining two sets $N1(T_1^*)$ and $N2(T_2^*)$ (lines 2 and 5). After the size has been assessed of the two sets $HC(T_1^*)$ and $NC(T_2^*)$, a check is performed to verify if this surpasses the critical value of 80%. If so, the function ends successfully, returning the values of S, T_1^* and T_2^*. Unfortunately, a reason for the checks to fail could be that of having chosen a too large duration S for the state of congestion of interest. This would mean that for many pairs of subsequent cars the following holds: the congested (or non congested) state a first vehicle incurs in does not last in time, as a second vehicle does not find the same state any longer. However, this could be a problem simply concerned with the duration of the S we have chosen, while a smaller value for S could exist, in principle, for which both the subsequent cars incur in the same state of congestion. The idea is hence that of looking for such value, by reducing S until a situation is captured where both the subsequent vehicles of the pair experience a similar state of congestion (or no congestion). This motivates the iterative structure of the `CTDF()` function. As a final note, it is important to consider that our experiments show that the difference between T_1^* and T_2^* is always confined within a 3% value difference. This is reasonable and largely expected, and justifies the fact that from now on we will only use a unique congestion threshold value T^*, obtained as $T^* = T_1^* \cong T_2^*$.

TABLE II. CONGESTION THRESHOLD DETECTION FUNCTION

Input: A list of traversal times.

Output: S, T^*.

1. $S \leftarrow \Delta_{max}$ minutes;

2. $(T_1^*, T_2^*) \leftarrow (T_1, T_2)$ s.t. `Max(`T_1, T_2`)`;

3. **while** $\neg$`Check1(`T_1^*`)` $\wedge\ \neg$`Check2(`T_2^*`)` $\wedge\ S > \Delta_{min}$ **do**

4. $S \leftarrow S - \delta$ minutes;

5. $(T_1^*, T_2^*) \leftarrow (T_1, T_2)$ s.t. `Max(`T_1, T_2`)`;

6. **end**

7. **if** $\neg$`Check1(`T_1^*`)` $\wedge\ \neg$`Check2(`T_2^*`)` **then**

8. **return null**;

9. **else**

10. **return** (S, T_1^*, T_2^*);

11. **end**

V. EXPERIMENTAL ASSESSMENT

We carried out a set of nine different experiments in 2008 and 2009 with a fleet of cars driving through traffic to verify the effectiveness of our mobility congestion detection and forecasting algorithm. Eight of these experiments were run in Los Angeles, CA, while one in Pisa, Italy. All the main information concerning these roads is listed in Table III (name, section, length, free flow traversal time, full and green traffic light cycles).Each vehicle carried an onboard system consisting of a laptop, a GPS receiver and an EVDO interface. Upon each traversal of a given road section R a car sent its traversal time to an ATIS, which, in turn, computed an estimate of T* when a sufficient amount of data was available. Our results are briefly described in the following Subsection.

A. Results

Our results are listed in Table IV where we reported, for each street, the number of times it was traversed, its congestion threshold T^*, the duration of its congestion S and the values of N and H (namely, the percentage of how many pairs of vehicles experienced stable congested and non-congested states, respectively). In addition, for each street we compare T^* to the delay a car would experience when traversing it and waiting for no more than a full red light time ($\hat{T} = T_{FFTT} + (CT - GT)$), assuming this a reasonable traversal time under non-congested conditions. Based on the results, the following observations are in order. Streets 1 through 5 all experienced alternated situations of congestion and non-congestion. The values of N and H confirm this conclusion, as they both surpass the 80% threshold. Moreover, for each of these streets the value of T^* is larger than the value of $\hat{T}$, which means that our algorithm found congestion threshold values above which cars really experienced congestion. Streets 6 through 8, instead, were deliberately chosen since they are empirically known as almost never congested. Our results corroborate this knowledge in two different ways. First, for each of these streets $\hat{T} > T^*$, thus proving cars almost always enjoy a smooth drive, due to the existence of a green wave. Second, the very small values of N confirm that no stable congestion was visible over those streets. Finally, street # 9 requires a different discussion. A high value of N and a small value of H seem to reveal a stable high congestion state. Despite this fact, $\hat{T}$ is greater than T^*. This paradox can be explained observing that as the traffic light at the junction with Sepulveda Blvd. permits to turn right on red, only very rarely our cars stood waiting for a full red light time. To prove this was the correct explanation, we performed a few more laps with cars going straight at that intersection. As expected, during such laps the value of T^* always exceeded that of $\hat{T}$. A more extensive set of experiments and results may be found in [18]. In conclusion, our algorithm was able to meet our expectations, detecting when congestion occurred and estimating its minimum persistence in time. As such, and thanks to its simplicity, we believe it is the ideal candidate to be integrated in modern ATISs.

VI. CONCLUSION

We introduced a simple general-purpose traffic congestion detection and short-term forecasting algorithm, validated on a real testbed driving over 450 miles. Our main contribution lies in the proposal of a new definition of congestion, where a street is defined as congested only when there is a high likelihood of it remaining in that state in the near future. This makes our definition easy to translate into an algorithm that results effective in providing significant results.

TABLE III. EXPERIMENT INFORMATION: LOCATION, ROAD SECTION, FREE FLOW TRAVERSAL TIME, TRAFFIC LIGHT CYCLE TIME AND GREEN TIME.

	Street	***Section***	***Length [m]***	***T_{FFTT} [s]***	***CT [s]***	***GT [s]***
1	***Via B. Croce***	***P.zza Guerrazzi-Via Queirolo, left***	***380***	***34***	***85***	***55***
2	***S.Monica Blvd.***	***Veteran-Sepulveda, left***	***380***	***61***	***120***	***15***
3	***S.Monica Blvd.***	***Wilshire-Roxbury, straight***	***280***	***17***	***90***	***54***
4	***S.Monica Blvd.***	***Wilshire-Bedford, right***	***390***	***30***	***90***	***54***
5	***Lincoln Blvd.***	***Fiji-Venice, back***	***2300***	***205***	***120***	***60***
6	***Wilshire Blvd.***	***Midvale-Westwood, right***	***130***	***7***	***150***	***80***
7	***S.Monica Blvd.***	***Roxbury-Bedford, right***	***100***	***7***	***90***	***54***
8	***Wilshire Blvd.***	***Veteran-Westwood, right***	***340***	***33***	***150***	***80***
9	***S.Monica Blvd.***	***Westwood-Sepulveda, right***	***680***	***75***	***120***	***50***

TABLE IV. ROAD DATA: NUMBER OF LOOPS, T^*, S, N, H AND $\hat{T}$.

	Street	***Section***	***# of loops***	***T* [s]***	***S [s]***	***N***	***H***	***$\hat{T}$ [s]***
1	***Via B. Croce***	***P.zza Guerrazzi-Via Queirolo, left***	***111***	***93***	***362***	***92%***	***84%***	***64***
2	***S.Monica Blvd.***	***Veteran-Sepulveda, left***	***134***	***175***	***608***	***80%***	***87%***	***166***
3	***S.Monica Blvd.***	***Wilshire-Roxbury, straight***	***77***	***62***	***987***	***94%***	***100%***	***53***
4	***S.Monica Blvd.***	***Wilshire-Bedford, right***	***77***	***82***	***987***	***92%***	***100%***	***63***
5	***Lincoln Blvd.***	***Fiji-Venice, back***	***30***	***354***	***900***	***100%***	***97%***	***265***
6	***Wilshire Blvd.***	***Midvale-Westwood, right***	***71***	***36***	***454***	***39%***	***98%***	***77***
7	***S.Monica Blvd.***	***Roxbury-Bedford, right***	***77***	***42***	***987***	***46%***	***83%***	***43***
8	***Wilshire Blvd.***	***Veteran-Westwood, right***	***71***	***74***	***454***	***37%***	***100%***	***103***
9	***S.Monica Blvd.***	***Westwood-Sepulveda, right***	***67***	***121***	***493***	***90%***	***54%***	***145***

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