**RTChoke: Efficient Real-Time Traffic Chokepoint Detection and Monitoring**

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**Abstract**—We present a novel efficient adaptive sensing and monitoring solution for a system of mobile sensing devices that support traffic monitoring applications. We make a key observation that much of the variance in commute times arises at a few congestion hotspots, and a reliable estimate of congestion can be obtained by selectively monitoring congestion just at these hotspots. We design a smartphone application and a backend system that automatically identifies and monitors congestion hotspots. The solution has low resource footprint in terms of both battery usage on the sensing devices and the network bytes used for uploading data. When a user is not inside any hotspot zone, adaptive sampling conserves battery power and reduces network usage, while ensuring that any new hotspots can be effectively identified. Our results show that our application consumes 40-80% less energy than a periodic sampling system for different routes in our experiments, with similar accuracy of congestion information. The system can be used for a variety of applications such as automatic congestion alerts to users approaching hotspots, reliable end-to-end commute time estimates and effective alternate route suggestions.

I. INTRODUCTION

Traffic congestion is a problem that most urban locales struggle to grapple with. In India, vehicle population has grown by over a 100 times in the last 50 years, while length of roads has increased by only 8 times [1] during this period. It is estimated that 4.8 billion hours of time and 1.9 billion gallons of fuel were wasted due to congestion in 2011 in the US alone [2]. While governments strive to curtail congestion through various methods such as car-pooling incentives and congestion pricing, the onus has fallen on individual users to best cope with it.

Recent research has focused on participatory sensing techniques for congestion detection as an alternative to infrastructure based systems that are often expensive and hard to maintain [3], [4], [5], [6]. In participatory sensing, users willingly contribute information from sensors they already own (such as those in their cell phones), which can be aggregated and analyzed at a central server. Here, mobile phones essentially behave as mobile sensors uploading information from where they are at any point in time. Unfortunately, proposed techniques using participatory sensing decouple collection of data from the use of the data, and often use periodic sampling and uploading from mobile phones. Depending on the period of sampling, this often results in oversampling in dense regions, leading to increased battery and network bytes usage on user’s mobile devices.

To this end, we formulate the following problem at an abstract level: given a set of mobile sensor devices, how do we collect GPS location information from them with low resource footprint, while deriving similar insights as uniform fine-grained sampling? We build on the observation that it is sufficient to selectively monitor certain key congestion hotspots. Our approach is to “couple” data collection with the use or utility of the data collected, i.e., more data is collected in places and at times where there is more utility than at other places and times. In fact, we observe through measurement studies that most of the speed variation with time on a person’s road trajectory is contributed by certain key hotspots. Key challenges, however, are to define what a congestion hotspot is in a generic sense, and to identify a hotspot reliably. Furthermore, congestion is a dynamic phenomenon, i.e., congestion hotspots may appear and disappear with time (e.g., due to accidents, construction, week-day office hours).

We design and implement a system RTChoke that consists of an Android application and a back-end analyzer that can automatically detect and monitor congestion hotspots. An adaptive sampling approach ensures that the emergence of new hotspots can be detected quickly as soon as they “become” hotspots, while also conserving critical battery power when the user is not driving within a hotspot zone. Further, a lightweight decision tree that uses a mix of sensors is used to detect if a user is driving, to automatically trigger location tracking using GPS and data upload to a central server. The central server utilizes the data uploaded by different smartphones and detects hotspots. We demonstrate that the system can make accurate estimates of user commute times and suggest efficient alternate routes and commute start times, based on information gathered at the hotspots, consuming only half the battery power compared to uniform monitoring tools such as Google Maps. Our results are consistent across users of our Android application in a large city in a developing nation, as well as in experiments using taxicab traces for San Francisco [7].

In summary, this paper makes two key contributions:

- **Building on the observation that it is sufficient to monitor certain key congestion hotspots, we first explore how to define a hotspot in a generic sense, and then describe how to continuously and automatically monitor and detect hotspots.**

- **We design an adaptive monitoring technique for mobile phones that detects if the user is driving a vehicle, and monitors GPS location or speed more frequently as we approach closer to the currently active hotspots,**
and less frequently when away from the hotspots; the farther we are from the hotspot, the lower is the sampling frequency. This effectively couples the data collection to their use, ensuring energy efficiency.

The rest of the paper is organized as follows. Section II formulates the problem, introduces the notion of hotspots, and discusses related work. Section III describes the design and implementation of RTChoke. Section IV provides analysis of our proposed approach. Section V presents performance evaluation of RTChoke. Section VI concludes the paper.

II. PROBLEM FORMULATION

In this section, we first motivate our solution approach through a simple experiment that shows the presence of traffic congestion hotspots. We then provide a formal definition of a hotspot, and discuss related work.

A. Motivation

Twelve employees from our organization used the smart phone application developed by us for two months, contributing location and speed information from their trips to and from office – hereafter we refer to this office location as TechPark (marked with a rectangle in the Fig. 1). The figure shows a heat map of average speed (points indicate only speeds less than 30 kmph) on a road stretch just outside the TechPark across all these trips. Fig. 1 shows that the average speed just outside the TechPark is mostly 5-15 kmph during the commute hours, indicating the presence of a chokepoint or a hotspot. The speed on the same road segment is greater than 30 kmph during afternoons and late nights.

To illustrate the nature and effect of congestion on commute times, we consider data from a single user (other users demonstrate similar trends). Over a period of two months, the user arrived at office each day at some time between 8:00 AM and 11:30 AM along the trajectory shown in Fig. 2. We studied the commute time to traverse the 2 km of his commute closest to the TechPark (referred to as Hotspot Zone in Fig. 2), and compared this with the time taken to traverse the rest of the distance from his home, which was about 6 km. Fig. 3 shows these two time-splits, namely, within the hotspot zone and outside the hotspot zone, for different times at which the user entered the hotspot zone. Outside the hotspot zone, the user covered a distance of 6 km in about 8 minutes on average. In contrast, the last 2 km of his commute took more than 15 minutes on average. Another interesting observation is that the variance in commute times is very low for the trip up to the hotspot, while the variance is considerably higher inside the hotspot zone.

The above observations form the primary motivation for our work. We ask ourselves the following questions. How do we define and automatically detect such congestion hotspots? Can we develop a smart phone application that will require no active user participation, consume minimal battery power, and yet provide automatic and accurate congestion estimates? Is it possible to tune the system parameters to meet user’s power budget constraints? We built a system that answers these questions in the affirmative.

We define a congestion hotspot as a geo-spatial region (specifically, a road segment of a certain length) with the following properties:

- **Current average speed** ≤ **τ** × **reference speed**, where **τ** is a predefined congestion threshold, and **reference speed** is a reasonable achievable speed in the region. In our implementation, we use the maximum speed observed as the reference speed.
- The region shows high temporal variance in average speed.
- The congestion at all points within the hotspot region is similar at all times.

While several studies exist that define other notions of congestion zones [8], [9], we find that our simple definition is sufficient in practice as typical congestion situations are contained within this zone.

B. Related Work

GPS and other sensors are widely used to achieve low-cost traffic monitoring. In this section, we briefly discuss recent studies, and describe how we advance the state-of-the-art.

**Participatory Sensing**: Participatory traffic monitoring can be broadly classified into vehicle-mounted and smartphone-based sensing. In vehicle-mounted sensing, location data is collected from moving objects that are mounted with GPS and other sensors [10], [11]. Examples of such sensing include: (a) **Green GPS** that computes fuel-efficient routes [12], (b) **Pothole Patrol** accesses road surface conditions [13], and (c) **Taxi durations and fare estimation** [14].

In smartphone-based sensing, users are generally provided with an application that automatically collects data from the smartphone sensors [15]. Mobile Millenium [3] and Nericell [6] utilize multiple sensors on smartphone, such as GPS, cellular connection and accelerometers, that detect traffic delays and congestion. A transit tracking system enables periodic GPS sampling if the user is moving in a vehicle, and then detects congestion is developed in [4], [5].

Similar to the above studies, RTChoke is a participatory sensing approach with minimal resource footprint, and minimal user intervention, which requires the user to primarily install and start the application once. Other applications providing similar services include Google Maps and Waze [16], but both of them do not adapt based on the data utility. Moreover, they require significant user participation.

**Traditional Road Traffic Engineering Models**: There is a large body of work in traffic control systems for detecting congestion, such as three-phase theory [8], Forecasting of Traffic Objects (FOTO) and Automatic Tracking of Moving Traffic Jams (ASDA) [9]. These systems typically require large amount of historical data to build reliable models, do not work for dynamic unpredictable hotspots, and require that traffic does not evolve significantly from the data for the models to remain valid.

III. DESIGN AND IMPLEMENTATION

Given a road network, and a system of mobile devices traveling on the road network, the goal of RTChoke is to (1) identify traffic congestion hotspots dynamically using data uploaded from the mobile devices, and (2) monitor the congestion hotspots continuously while being efficient in terms of battery and network resources utilized on the mobile devices.
Several applications such as automatic congestion alerts to travelers, end-to-end commute time predictions, alternate route suggestions can be instantiated over RTChoke.

For tractability, RTChoke considers that a road network is broken down into road segments (including lines and curves) [17]. Each road segment is a geospatial region that is tagged as a hotspot when it satisfies the conditions described in Section II. To achieve the conflicting goals of maintaining reliability of tagging a region as a hotspot, and reducing the overhead of maintaining too many road segments, one needs to strike a tradeoff on the length of the road segments. For instance, longer segments (especially on highways) reduce the total number of road segments, but may be inaccurate in capturing congestion if only parts of the segments are congested during busy hours. To balance this tradeoff, RTChoke assumes that these segments are of 10s to 100s of meters. One side-effect of this tradeoff, however, is that adjacent road segments can be completely correlated at all times; in such scenarios, RTChoke considers only one of the correlated segments as a representative hotspot, and avoids maintaining information or monitoring the other segments.

A. Solution Overview

We now describe the overall architecture and process of RTChoke, pictorially shown in Figure 4. A smart-phone runs an application in the background to selectively sample GPS and upload the location data to the server in real time. On the phone, an activity classifier is invoked every 30 seconds to detect a user’s activity. If the user is driving, it invokes Congestion Hotspot Retriever to obtain current congestion hotspot information from server, and Sampling Rate Estimator to adapt GPS sampling interval based on the nearest congestion hotspot. Once a location sample is obtained from GPS, it is uploaded to the server by the Data Uploader. The server receives location updates and passes them to a Daemon. The Daemon validates each location and maps it to a point on the road as indicated by the Map-Matching Module. Map-matching corrects the GPS sampling errors and snaps the location samples to the roadpaths traveled. In the current implementation, we use a Hidden Markov Model based map-matching [18]. User’s information along with the updated location is placed into a spatio-temporal data structure, which is used by the Congestion Estimator to detect congestion hotspots.

RTChoke’s functionality can be mainly categorized into two components: (1) detecting that a road segment is a hotspot, and (2) monitoring at the hotspot frequently, while also monitoring non-hotspots less frequently to be able to detect new hotspots. We describe each components now.

B. Hotspot Detection

Hotspots can be detected using different approaches. A majority of them rely on parameters such as maximum speed limit on a road or number of lanes [9]. While such parameters are easily available for roads in developed countries, they are either not defined, or changing over time, or not followed strictly in the developing countries. Further, these parameters are not sufficient to detect congestion caused by occasional incidents such as accidents or minor road works. Thus, to detect new congestion hotspots automatically, we do not assume knowledge of any such parameters. Instead, we use dynamic speed information received at the server for each road-segment over a long term to infer a reference speed, and view the current speed samples in relation to the reference speed.

RTChoke also recognizes that congestion is a dynamic phenomenon on a road segment, which varies based on the the spatial location of the road segment, time-of-the-day and unpredictable road incidents such as accidents and construction. We now describe how RTChoke accounts for the spatio-temporal features of congestion and road dynamics to tag the road as a hotspot.

1. Accounting for temporal variability of speeds: The speeds on the roads vary based on temporal aspects such as time-of-the-day. To capture these temporal effects we divide a day into 48 equal time-bins, each representing 30 minutes. For each road segment, we capture the number of samples received and average speeds. The server also maintains a maximum speed per segment across all times of the day. At each bin, we categorize congestion hotspots using low-, medium-, and high-congestion levels, similar to [8].

2. Hotspot Marking: A time-bin of a road-segment can exist in three states: uncongested, possible hotspot and hotspot. We initially set all road-segment bins to uncongested state. As the user data trickles down to the server, the server updates the
average speeds. Based on the aggregated values, the server classifies the road into one of the three states.

Road segments may also experience flash-congestion due to incidents such as accidents or temporary obstructions. Automatic detection of flash hotspots is valuable since it can provide early warnings to users approaching the hotspots. To detect flash congestion, it is important to have a bounded sampling interval that is not larger than the time the user may take to cross the incident zone. When multiple recent samples with low speeds are obtained, the server tags the road-segment as possible hotspot. The server requests clients to increasingly sample road segments to conclude if the possible hotspot segment is in fact a hotspot. We analyze the time required for flash-congestion detection in Section IV-A.

3. Separating hotspots from inherently low-speed roads: Different roads may have different speed signatures depending on the road size and road-surface conditions such as speed-bumps and pot-holes. Thus, low average speeds do not necessarily imply that the road-segment is a congestion hotspot. We distinguish congestion hotspots from roads with inherently low speeds.

For each road-segment, we keep track of the maximum speed, $V_{\text{max}}$ observed in the past. We then tag a segment as hotspot if the current average speed for the time-bin is lower than a threshold $T_{\text{hot}} = 0.25 \frac{V_{\text{max}}}{2}$. We set two more thresholds: $T_{\text{med}} = 0.5 \frac{V_{\text{max}}}{2}$ and $T_{\text{low}} = 0.75 \frac{V_{\text{max}}}{2}$. We tag the segment as medium- or low-congestion if the speeds are between $[T_{\text{hot}}, T_{\text{med}}]$ or $[T_{\text{med}}, T_{\text{low}}]$, respectively. We obtain these thresholds based on observations made from experiments at TechPark.

C. Hotspot Monitoring

For energy efficiency and minimizing the network usage, the application running on a smart phone detects when the user is mobile, and only then starts the monitoring activity. It adapts the monitoring frequency based on the distance from the hotspot. If multiple hotspots are close to the mobile device, the closest hotspot determines the monitoring frequency.

1) Decision-Tree based Activity Detection: Activity detection allows the system to be completely automated, thus not requiring active user participation; this is an important design goal for RTChoke to ensure that people continue to use the application for a long time. Activity detection should accurately identify if a user is driving. False-positives in detection leads to excessive energy drain since the app will sample when the user is not driving (which is generally true for most of the day). False-negatives lead to loss of valuable data at the server side to detect hotspots.

We use an energy-aware combination of approaches for activity detection [4], [19]. We switch-on and sample GPS only when the user is most probably driving. Figure 5(a) shows our classification mechanism. We employ a decision tree where we first attempt to find clues of vehicular movement without sensing. Specifically, we first check if the user is within the range of any known WiFi (office/home) access points. In such a case, the user is most likely not in a vehicle. Otherwise, we check the number of GSM cell-towers associated with the user’s cell-phone in a given time window; if the number of towers is more than three in a short amount of time, we detect that the user is moving. Otherwise, we use accelerometer readings to determine if the user is driving (as shown in Figure 5(b)) [4].

2) Utility-aware Sampling: Once the activity classifier detects that the user is moving in a vehicle, GPS sampling is enabled. However, the utility of GPS samples vary spatio-temporally, based on the current distribution of hotspots. Each phone periodically polls the server when the user is driving, to obtain a current list of congestion hotspots, where each congestion hotspot is defined in terms of its latitude and longitude based location, and approximate distance for congestion spread, $d_{\text{in}}$. Based on this information, the phone selects the next GPS sampling interval $y$ as:

$$
y = \begin{cases} S_{\text{min}}, & \text{if } d \leq d_{\text{in}} \\ S_{\text{min}} + (1 - \frac{d}{S_{\text{max}} - S_{\text{min}}}) (S_{\text{max}} - S_{\text{min}}), & \text{if } d > d_{\text{in}} \end{cases}$$

(1)

where $d$ is the distance between the phone user and the closer end-point of the nearest hotspot, and $S_{\text{min}}$ and $S_{\text{max}}$ are the minimum and maximum sampling interval for GPS. If the user is within the congestion zone, then GPS is sampled at higher frequency. Otherwise, GPS is sampled adaptively, as the data becomes less useful. Values of $S_{\text{min}}$ and $S_{\text{max}}$ can be selected based on a power-budget for the application, which is described in more detail in Section IV. $S_{\text{max}}$ provides a bound on the GPS sampling interval, which is useful in detecting new congestion hotspots.

The system supports querying the congestion level at a given location and at a given time. The location data uploaded by the phone is recorded in a spatio-temporal data structure. We use road network information to maintain spatial information [17]. To maintain temporal congestion information, we record the speed on roads at different times of the day. This allows the system to notify details such as hotspot location during a particular time of the day, and time required to cross it to the user.

IV. ANALYSIS

In this section, we analyze the hotspot detection approaches and utility-aware adaptive sampling.

A. Hotspot Detection

Consider a road segment $R$ where congestion builds up due to an incident, such as an accident, at time $t = 0$. We compute
the time taken for the server to detect that the segment might be a possible hotspot. Let $S$ be the current sampling interval on $R$ given the location of existing hotspots (derived from Equation 1).

We assume that the server tags the segment as a possible hotspot if it receives $N$ samples. We also assume that the communication of speeds from the application to the server is error-free. We first compute the number of vehicles that are on the road segment as a function of time, and then estimate the time required for the server to receive $N$ samples.

1. **Vehicle build-up function**: We denote the rate at which the vehicles enter the road segment $R$ by $r_{in}$ vehicles per unit time. Let $r_{out}$ be the rate at which the traffic exits the hotspot. We assume that $r_{out} \leq r_{in}$ at $R$, and hence the queue dynamics leads to infinite buildup until the traffic regulators defuse the congestion by external means. Our aim is to estimate the time required to detect congestion buildup, and thus provide a framework to notify flash congestion to travelers and regulators.

The number of vehicles that accumulate on $R$ in time $t$ is given by $c(t) = (r_{in} - r_{out})t$; the congestion buildup increases linearly.

2. **Number of samples at time $t$**: We now estimate the number of samples that the server receives at a given time $t$. Since one car sends the sample every $S$ time units, the expected number of samples at time $t$ from $c(t)$ is $\frac{c(t)}{S}$. Hence, over a period $[0, t]$, the total number of samples received at the server is defined by

$$n(t) = \int_0^t \frac{c(x)}{S} \, dx = \frac{(r_{in} - r_{out})t^2}{2S}.$$  \hspace{1cm} (2)

The time required for the server to collect $N$ samples to detect if $R$ is a possible hotspot can be determined by equating $n(t) = N$. Hence,

$$T = \sqrt{\frac{2NS}{r_{in} - r_{out}}}.$$  \hspace{1cm} (3)

Hence, the time required to detect a road segment as a hotspot at the server decreases drastically, as a square root function of differential of the rates at the segment.

Figure 6 shows the time required to detect a hotspot where $N = 30$, $S = S_{max} = 2$ minutes, and for different $r_{in}$ and $r_{out}$. Rates are measured in vehicles per minute, and are derived from existing traffic literature [20]. As the difference in the entry and exit rate increases, the detection time for congestion decreases rapidly. Once the server detects the congestion hotspot, regular adaptive sampling can be resumed.

B. **Energy budget for Adaptive Sampling**

We have modeled the energy consumption of adaptive sampling. We use the analysis to choose appropriate values for the parameters in our adaptive sampling approach for our experiments. Due to space constraints, we briefly sketch the results of the model. Detailed derivation can be found in the extended paper [21].

Recall that the vehicle samples with a periodicity of $S_{min}$ when it is within the congestion zone. Outside the congestion zone, the sampling interval is as shown in Equation 1. Hence, the energy used for a user trip is a function of the number of samples inside and outside the congestion zone (denoted respectively by $n_{in}$ and $n_{out}$). The distance traveled inside and outside the congestion zone is denoted by $d_{in}$ and $d_{out}$, respectively.

The total energy used by the application for the entire trip ($E$) is given by

$$E = n_{in}e_{in} + n_{out}e_{out},$$  \hspace{1cm} (4)

where $e_{in}$ and $e_{out}$ is the average energy spent per sample inside and outside the congestion zones, respectively. Note that these energy includes the amount of sensing, computation and communication incurred, which is in-turn a function of the nearby congestion zones (as described in the section III-C).

Let $v_{in}$ and $v_{out}$ denote the average speeds inside and outside the congestion zones. Then $n_{in} = \frac{d_{in}}{S_{min}v_{in}}$, as sampling is uniform inside the congestion zone. We also show that $n_{out} = 1 + \left[ \log_r \left( 1 + \frac{d_{out}(r-1)}{v_{out}S_{min}} \right) \right]$, where $r = \frac{d_{in} + v_{out}S_{max}}{d_{in} + v_{out}S_{min}}$.

Based on average values from our local city experiments, we obtained the average speed within the congestion zone as $v_{in} = 2$ m/s (16.67 kmph), and the average speed outside the congestion zone as $v_{out} = 12.5$ m/s (45 kmph). The energy consumed per sample were obtained as, $e_{in} = 0.4$ J and $e_{out} = 7$ J (note that $e_{out}$ is for a much larger time period as samples are obtained less frequently). We plot the energy as a function of the maximum sampling interval (as derived in Equation 4), for different values of the congestion zone radius $d_{in}$ and different minimum sampling intervals in Figure 7, assuming that the total distance covered by the user in the trip is $d_{in} + d_{out} = 10$ km.

![Figure 6: Hotspot detection time decreases rapidly as $r_{in} - r_{out}$ increases.](image)

**Fig. 6.** Hotspot detection time decreases rapidly as $r_{in} - r_{out}$ increases.

**Fig. 7.** Total energy consumed by the apps.
energy consumption is sensitive to the congestion zone radius, as this is where a majority of the samples are obtained. For the same reason, the sampling interval within the congestion zone also has a considerable affect on the energy consumed. For our experiments, we used \( d_{in} = 2000 \) m as we observed that most congestion situations were contained within this stretch. The smart phones used in our experiments had battery energy of about 18 kJ and we set a goal for RTChoke that the application should not use more than 3% of the battery charge, which amounts to 560 J. Based on this constraint, we choose \( S_{min} = 1 \) s and \( S_{max} = 120 \) s for our experiments.

V. EXPERIMENTAL EVALUATION

We evaluate RTChoke using two sets of data. The first set was obtained from a pilot study of 12 smart-phone users commuting to and from their workplace at TechPark, located in a major city in a developing country, over a period of almost 2 months. The second set was traces of taxicab location information in San Francisco city [7].

A. Congestion at TechPark

In Section II, Figures 1 and 3, showed that the roads close to TechPark experienced much lower average speeds during peak hours than roads that were farther away and that the observed speeds varied significantly with time of day. In our evaluation, we show: (1) RTChoke can accurately detect congestion hotspots that exhibit low average speeds as well as temporal variation, (2) Effectiveness of adaptive-sampling compared to continuous sampling, and (3) Comparison of the energy footprint of our application with that of Google Maps with traffic updates enabled. For these experiments, we set \( d_{in} = 2000 \) m, \( S_{min} = 1 \) s, and \( S_{max} = 2 \) min, adhering to the analysis presented in Section IV.

1) Real-time Congestion Detection: The TechPark region (highlighted with a blue rectangle in Figure 1 in Section II) hosts multiple organizations employing more than 100,000 people. As noticeable in the figure, the average speeds just outside TechPark are quite low during peak hours due to severe congestion. Based on real-time feeds obtained from smartphone users, we were able to identify segments of congestion and classify them into three levels (level 1 represents low congestion and level 3 represents high congestion). This is shown as a heat-map in Figure 8, demonstrating RTChoke’s effectiveness in detecting hotspots.

Another key observation, is that Figure 8 shows that the region inside the TechPark is not congested, although Figure 1 shows the average speeds on these roads to be low (inside the blue rectangle). In fact, these roads are indeed not congested, and the low speeds are due to narrower roads with speed bumps every 20 meters. As speeds are uniformly low and there is no significant difference between the current observed speeds and the maximum reference speed for the road-segments, we do not classify them as congestion hotspots. This is in line with our aim of monitoring only those regions with high variance in speeds, and not waste critical battery energy monitoring areas with uniform speeds (we can afford to obtain samples at a lower frequency). RTChoke was able to distinguish such areas with uniformly low speeds from actual congestion hotspots that exhibit a large deviation between the current observed speeds and the maximum speed for that road-segment.

In addition to detecting hotspots, high sampling rate near the hotspots ensures that we obtain sufficient samples around the hotspot region to be able to accurately characterize temporal variance at the hotspot as shown in Figure 3.

2) Adaptive vs. Continuous Sampling: Next, we evaluate the overhead and accuracy of RTChoke with continuous and adaptive GPS sampling. For the continuous mode, GPS was sampled every second (same as \( S_{min} \) for adaptive sampling). We consider a trip of 15 km from TechPark to user home. Congestion zone is a circle with 2 km radius outside the TechPark (as shown in Figure 8).

Figure 9 shows how the sampling interval increases sharply (based on adaptive sampling) as a typical user moved away from the hotspot zone. The sampling period is multiplicatively increased from \( S_{min} \) as the user moves away from the hotspot. As shown in Figure 10, adaptive sampling yields about \( 9 \)× improvement in terms of the overhead, captured as the number of GPS samples collected and uploaded.

We now discuss the accuracy of adaptive sampling. We define the accuracy as the time when the user is detected to have entered the congestion zone when using adaptive sampling as compared to the app using continuous GPS sampling. We compare the time when the congestion zone was entered for 3 trips from user home to TechPark (reverse of the above trajectory from office to home) since it is a harder case to detect entrance. We observed that the adaptive sampling took additional 45 seconds on an average to detect that the user has entered the congestion zone when compared to the continuous sampling, which is merely 4.8% of the total time spent by the user in the congestion zone.

3) Energy Footprint: We compare the energy footprint of RTChoke with Google Maps app with real-time traffic updates enabled. To estimate application-specific energy consumption, we use PowerTutor [22], which provides per-application energy consumption by different components, such as CPU, 3G, and LCD screen. Google maps with traffic updates enabled, can be used to view the status of congestion on different roads. Unlike the adaptive sampling of RTChoke, Google maps samples GPS continuously and uploads location data in real-time to the server. It retrieves traffic information in terms of low-, medium-, and high-speeds from their server(s). The only additional operation performed by Google maps is retrieving map-specific data. RTChoke does not require map-specific information for its functioning. For fairness of comparison, we perform the experiment by running RTChoke and Google maps on two identical HTC Desire smartphones, both carried
by the same user. Also, we subtract the LCD screen specific energy consumption from the total energy to measure only the energy consumed by the application.

Figure 11 compares energy consumed by RTChoke and Google maps over time, when a user (carrying both the phones) is moving away from a congestion hotspot. Note that for the first 170 seconds, the user is within the congestion zone, where RTChoke samples and uploads at the peak rate. Thus, RTChoke consumes almost as much energy as Google maps. However, Google map’s energy consumption increases almost linearly even beyond the congestion region, but energy for RTChoke grows much slower because of adaptive sampling.

We also measured the total uplink traffic from RTChoke and Google maps (graph omitted in the interest of space). The total bytes uploaded by Google maps was 85.5 KB, whereas RTChoke uploaded 19.36 KB data, a reduction in network usage by about 4.5 times.

To avoid route-specific biases, we also compared the average energy consumption for three different routes with different travel durations as shown in Figure 12. It can be observed that the difference in energy consumption between Google maps and RTChoke is higher when the duration of travel away from a congestion hotspot is higher, as demonstrated by Route-1 and Route-2. When the user is traveling a longer distance outside the congestion hotspot (8 km away for Route-3), adaptive sampling yields an order of magnitude lower energy footprint compared to that of Google maps.

**B. Congestion in San Francisco**

We analyzed location information from 200 cabs across 3300 road segments in San Francisco city using the CRAW-DAD data [7]. Each cab reports GPS coordinates and timestamp once every minute. We process this data as explained in Section III to estimate the congestion in SFO city.

We use the temporal speed data per road-segment to compute the congestion levels in SFO city. The median average speed on road-segments is around 45 km/h (or 28 mph). Fig. 13 shows the temporal variance of hotspots in SFO city; the number of hotspots vary with the time-of-day showing peak and off-peak traffic. Fig. 14 shows the congestion heat-map at peak traffic (at 17:00), with hotspots marked in red. Only 137 roads (approximately 4% of all roads sampled) were tagged as hotspots, where users should expect large delays due to lower speeds. During the off-peak hours the number of congested road-segments was even smaller. A more complete spatio-temporal variation of congestion in SFO can be found in our technical report [21].

Similar to TechPark data, we observed that hotspots demonstrated a much larger variation in speeds when compared to the other road-segments. In order to measure how the road-speeds vary in congestion hotspots, we compute the Normalized Deviation (ND) of each road-segment, defined as the ratio of the standard deviation to the average speed on the road-segment. Fig. 15 plots the CDF of ND for hotspots and non hotspots. The figure shows that hotspots have larger values of ND, and hence larger temporal variation.

Fig. 16 shows the trajectories followed by two cabs at 17:05 and 17:16 on the same day. It also shows the average speed of the roads between 17:00 to 17:30. A square marks the congestion hotspot. Note that the cabs were traveling much faster outside the hotspot than closer to it.

We recommend actively monitoring a small number of hotspots instead of all road segments based on our observation that deviation in speeds is higher at hotspots and lower at non-hotspots. For non-hotspots, average speeds at the given time-bin over all history can be used as an approximate speed.
Such selective monitoring of hotspots with high frequency can be used for low-complexity and energy-aware congestion monitoring for applications (e.g., alerting users about possible congestion and suggesting alternate routes). Adaptive Sampling approach suggested in Section III-C2 utilizes this insight to monitor frequently at the hotspots, and to save energy by low-rate monitoring at other road-segments.

**Flash congestion detection:** We now compare the time required to detect flash-congestion. We simulate flash-congestion caused by an accident, in which all the cars approaching the accident location get blocked. We use the real location traces for cars from the San Francisco cabs data set. We assume that multiple cars (as varied on X-axis) need to report low speeds to detect congestion reliably. We consider $S_{\text{min}} = 1$ minute (the minimum granularity of samples in the data set) and $S_{\text{max}} = 2$ minutes. Since there was no congestion before, we use $S_{\text{max}}$ as the cars’ sampling interval. We consider two types of alerting modes: Regular and Expedited. In the Regular mode, cars do not change their sampling interval until congestion is detected reliably. On the other hand, in the Expedited mode, the server declares that a reported location is a possible congestion hotspot, if even a single car notifies lower speed than threshold. In such a case, the server notifies the other cars approaching the same possible congestion point to sample at peak rate (at $S_{\text{min}}$).

Fig. 17 plots the time required to reliably detect flash-congestion after the first car has notified a lower-speed value than the congestion threshold. It can be seen that the time to detect flash congestion can be reduced by up to 50x using Expedited alerting mode. The significant increase in congestion detection time from that for 5 versus 10 or 15 cars is due to the cabs arrival rate in the dataset.

**VI. Conclusion**

In this paper, we show that in a traffic monitoring system built over mobile sensors, automatically detecting and monitoring congestion hotspots can significantly reduce the overall overhead of the system, without compromising on the accuracy, in comparison, to a system with fine-grained periodic monitoring. The solution, RTChoke, requires minimal user intervention, and optimizes both battery power and network bytes used for data uploads. We believe that detecting hotspots and monitoring congestion just based on hotspots makes participatory sensing traffic applications efficient by coupling collection and use of data.

**REFERENCES**


