Road Traffic Congestion in the Developing World

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ABSTRACT

Road traffic jams continue to remain a major problem in most cities around the world, especially in developing regions resulting in massive delays, increased fuel wastage and monetary losses. Due to the poorly planned road networks, a common outcome in many developing regions is the presence of small critical areas which are common hot-spots for congestion; poor traffic management around these hotspots potentially results in elongated traffic jams. In this paper, we first present a simple automated image processing mechanism for detecting the congestion levels in road traffic by processing CCTV camera image feeds. Our algorithm is specifically designed for noisy traffic feeds with poor image quality. Based on live CCTV camera feeds from multiple traffic signals in Kenya and Brazil, we show evidence of this congestion collapse behavior lasting long time-periods across multiple locations. To partially alleviate this problem, we present a *local de-congestion protocol* that coordinates traffic signal behavior within a small area and can locally prevent congestion collapse sustaining time variant traffic bursts. Based on a simulation based analysis on simple network topologies, we show that our local de-congestion protocol can enhance road capacity and prevent congestion collapse in localized settings.

Categories and Subject Descriptors

I.4.9 [**Computing Methodologies**]: Image Processing and Computer Vision—*Applications*; I.6.3 [**Computing Methodologies**]: Simulation and Modeling—*Applications*

General Terms

Algorithms, Measurement

Keywords

traffic congestion, traffic detection, congestion collapse, simulation

1. INTRODUCTION

Poor road traffic management is the primary reason for extended periods of traffic congestion throughout the world. As per Texas Transportation Institute's 2011 Mobility report [1], congestion in the US has increased substantially over the last 25 years with massive amounts of losses pertaining to time, fuel and money. Sã o Paulo, Brazil is known to experience the world's worst traffic jams [32], where people are stuck for two to three hours everyday in traffic jams. The issue of traffic congestion has affected both the developing and developed economies to different degrees irrespective of the measures taken to curb the issue.

A common feature across road networks in many urban regions in the developing world is the presence of critical congestion areas; we refer to a critical congestion area as one where a network of roads converge and a large amount of traffic needs to traverse the common congestion area. As per free-flow traffic theory [43], a free flow traffic road segment can be associated with a traffic curve where the traffic exit rate is a function of the traffic density in the road segment. A free-flow road segment is known to exhibit a *critical density* point where any traffic input that pushes the density beyond the critical value can trigger a "spiralling effect" that results in the road segment operating at a low-capacity equilibrium point. Worse still, small traffic bursts over short time periods can potentially trigger the spiralling effect resulting in a congestion collapse. Many critical congestion areas in developing regions have poor traffic management systems that if any of these critical congestion areas hits a congestion collapse, the road network can result in a massive traffic jam for elongated time periods.

In this paper, our goal is to design mechanisms to detect the state of traffic congestion in and around critical congestion areas and also design simple preventive mechanisms to prevent critical congestion areas from hitting congestion collapse. In this paper, we describe a simple image processing algorithm that can be used to analyze CCTV video feeds from traffic cameras to detect congestion levels in real time. Using this algorithm, we show evidence of actual congestion collapse across multiple locations in São Paulo, Brazil and Nairobi, Kenya. Specifically, we show congestion collapse scenarios that last for multiple hours at important junctions in Nairobi and São Paulo. Our congestion detection image processing algorithms have been specifically designed for highly noisy traffic camera feeds and differ in spirit from conventional traffic image processing techniques which typically rely on high quality traffic images [41, 44, 39].

To partially alleviate this problem, we propose a *local de-congestion protocol* that coordinates traffic signal behavior within a possible critical congestion area to prevent the *critical tipping point* behavior. The goal of the local traffic signal coordination is to maintain the traffic density in the congestion area below the critical density value. Our local de-congestion protocol coordinates the traffic signals that control the input flow within the congestion area and ensures that the local traffic density does not cross the critical tipping point. Based on a simulation-based study across simple real-world road network topologies, we show that our local de-congestion protocol can prevent congestion collapse in the face of bursty traffic arrivals and can enhance the road network capacity during such congestion. We believe that our local de-congestion protocol can be deployed around potential congested areas resulting in preventing congestion collapses and thus, maintaining a healthy input and output rate during congestion. Our local decongestion protocol is primarily designed for small congestion areas and is orthogonal in design to many of the conventional intelligent signaling solutions proposed in the transportation literature [17, 5, 9, 21, 14, 31, 3]. While our solution is by no means optimal, an advantage of a localized approach is that the decongestion protocol is easily deployable in critical congestion areas to enhance the operational capacity during a congestion collapse.

2. POOR TRAFFIC MANAGEMENT

Cities throughout the world have found themselves at the brink of massive traffic explosion, hence curtailing their ability to manage traffic. The situation has worsened for developing regions due to the following reasons:

Unplanned cities: Roads tend to be narrow and poorly built. As cities grow in an ad-hoc manner, no provision is made towards scaling road capacities, eventually resulting into several bottleneck roads, which remain congested for extended periods of time. Furthermore, many developing countries have witnessed an explosive growth in their vehicular population resulting in a failure of conventional traffic management strategies.

Poor discipline: Drivers often are not trained sufficiently to follow lane discipline. The impact of poor lane discipline, especially at traffic junctions, deteriorates the already overcrowded junction situation. Furthermore, drivers frequently jump red lights and block the intersection, causing further traffic congestion. These problems are compounded by the fact that traffic law enforcement is poor, thereby providing no incentive for drivers to follow the rules.

Alternate traffic means: Countries with fast growing economies have witnessed a surge in the number of vehicles across major cities. These cities seldom have efficient mass transit systems, forcing people to operate private vehicles. This problem is compounded by the social stigma, where people view operating a private vehicle as a sign of prosperity, while public transport is viewed as being used by the lower echelons of society.

Archaic management: Traffic junctions are often unmanned, thereby allowing drivers to drive in a chaotic manner. Even if a junction is controlled by a cop or a traffic light, the traffic junctions are largely independent of any traffic management strategy, only optimizing the respective junction traffic flow, in the direction of maximum traffic build up. Furthermore, these approaches enhances traffic mismanagement in already congested roads, accelerating congestion collapse (see §3).

Tighter budgets: A significant amount of investment is required to set up a traffic management infrastructure which can scale with the increasing traffic. Such an infrastructure not only involves measuring and analyzing real-time traffic data but also focuses towards enhancing congestion detection, solving real time congestion and forecasting congestion scenarios. In developing countries, ravaged by corruption and bureaucracy, there are multiple hurdles before the money actually progresses towards such large initiatives.

In this paper, we specifically make the case that while increasing road capacity is useful, it is not the only way to mitigate traffic problems. By smart flow-control techniques in present infrastructure, it is possible to increase the operational capacity of the existent road system.

Figure 1: The first picture, taken at 5:15pm shows an empty road in Rio de Janeiro, Brazil. Barely 5 minutes later, the road is completely jammed up.

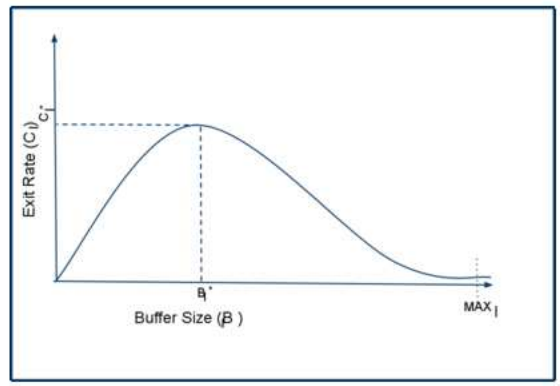

Figure 2: The traffic curve showing the relationship between traffic density and operational exit rate.

3. CONGESTION COLLAPSE

Fig.1 shows two pictures from a traffic feed from the Rio-Niteroi bridge in Brazil. The first picture taken at 5:15pm shows traffic flowing smoothly, with absolutely no congestion. The second picture, taken barely 5 minutes later, shows that congestion has set in, leading to a traffic jam lasting for two hours. This illustrates the basic fact that once congestion sets in, it takes a long time to be resolved.

To understand why traffic congestion sets in quickly, and also takes long to dissipate, we need to understand the concept of a traffic curve, as explained next.

3.1 Traffic Curve

In this discussion, the terms *road* and *link* are used interchangeably. There are several metrics that define traffic characteristics such as speed, flow and density of a link. Consider any link with two points with traffic free-flowing across them. Each link is associated with a traffic density representing the number of vehicles in the link. The operational free-flow exit rate of a link varies with the traffic density. The *traffic curve*, illustrated in Fig. 2, captures the variation between these two parameters. At high traffic densities (signifying traffic jams), links have very low operational exit rates and at low densities, the exit rate varies linearly with the traffic density. Each traffic link reaches an optimal capacity at a corresponding optimal operating density.

To formalize this notion, there are a few parameters that describe the state of a link l:

- Capacity: This is the maximum number of vehicles that the link can hold. It does not vary over time, and is represented as MAX_l.

- Buffer size: This is the number of vehicles on the link at any given point of time. However, traffic density is defined as number of vehicles per unit of road. Thus, buffer size is simply a multiple of traffic density(x *link length*). Hence, the terms *buffer size* and *traffic density* are used interchangeably, represented as B_l.

- Exit Rate: This is the rate at vehicles can exit a link, and is represented as C_l. As mentioned earlier, it depends on MAX_l, as well as B_l.

The traffic curve behavior has been well documented by the Intelligent Transportation Systems (ITS) community [43]. From the curve, we see that for low buffer sizes, the exit rate increases as the traffic density increases. Beyond a certain point, however, congestion takes place, and the exit rate of the link reduces. The point at which this transition takes place has the highest exit rate, denoted by C_l^*. The corresponding traffic density is denoted by B_l^*. Previous research has shown that B_l^* is approximately equal to $\frac{MAX_l}{3}$ [43].

Consider the case when the traffic density is B_l^*, and hence the exit rate is optimal at C_l^*. If a short burst of traffic enters the link and temporarily pushes the traffic density B_l to be more than B_l^*, the exit rate C_l will drop below C_l^*; this decreased exit rate will further increase B_l. This domino effect leads to the exit rate decaying rapidly, and we call it *congestion collapse*.

An important point to note is that even if the input rate is greater than the maximum exit rate C_l^*, congestion does not take place until the traffic density becomes greater than B_l^*. Consider a congested link whose B_l value is greater than B_l^*. Even if the input rate is reduced to below C_l^*, we are not guaranteed to get rid of the congestion in a short period of time, because the exit rate C_l at a traffic density of $B_l > B_l^*$ will be lesser than C_l^*. This is the reason that once congestion collapse takes place, it stays that way for long periods of time.

Thus emphasis of the curve analysis lies in not letting the B_l value of a link to get greater than $B_l^* - \epsilon$ for a small constant ϵ. A small burst of traffic ϵ, even for a short period of time, is sufficient to push the link into congestion collapse, as illustrated in Fig.1.

3.2 A simple example

To better understand how congestion collapse happens, we consider a simple example of 2:1 merge where two free-flow roads merge; this is a common occurrence in road networks. A simple example is illustrated in Figure 3 where vehicles in L are merging with the stream of vehicles on H. This simple example can be viewed at multiple granularity's: two lanes in the same freeway merging into a single lane or two separate free-flow roads merging. To visualize this problem from the perspective of traffic curves, consider three links in the setup:(a)H_{bef} representing,a small segment of H (covering a short distance of up to 0.5 miles) before the merge point; (b) a small segment L before the merge point; (c)H_{aft}, representing a small segment of H after the merge point. Each of the links can be associated with their corresponding traffic curves. Since we are dealing with a discrete version approximation using traffic curve, we should choose reasonable lengths to have meaningful buffer values for the links.

We primarily concentrate on two specific parameters of H_{aft}: $C_l^*(H_{aft})$ and $B_l^*(H_{aft})$. If the sum total of the exit rates of H_{bef} and L is always less than the optimal exit rate $C_l^*(H_{aft})$, then the merging never faces a congestion problem. If however, the sum of the input rates of L and H_{bef} is larger than $C_l^*(H_{aft})$, then the buffer size of H_{aft} grows. If the buffer of H_{aft} grows beyond $B_l^*(H_{aft})$, then the exit rate of H_{aft} begins to drop thereby, triggering the spiralling effect. Figure 3 shows how a small burst in traffic beyond $C_l^*(H_{aft})$ is sufficient to drive the system to operate at a low-capacity point. Once reached, the system will continue at this operational point and if the total input rate is greater than the operational exit rate, the congestion increases and spreads into the links H_{bef} and L.

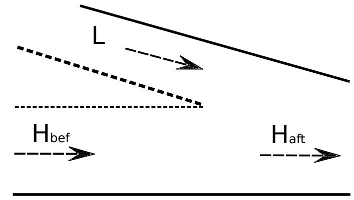

Figure 3: A sample topology illustrating a 2:1 merge scenario.

4. DETECTING TRAFFIC CONGESTION

The first step in mitigating traffic congestion is to estimate the amount of traffic on the link at any given point of time. A common method is to place sensors on the road and count the number of times they are actuated by the passing wheels of a vehicle. This approach suffers from four main problems: a) it is expensive to deploy, as the sensors need to be partially embedded in the tarmac, b) the sensors on the road are prone to theft, c) sensors need to be placed at multiple entry and exit points on the road, to maintain accurate counts, and d) even on a single stretch of road, the sensors need to be placed at regular intervals so as to estimate the density on different segments of the road.

A number of highways constructed in the previous decade contain CCTV cameras to monitor the real-time traffic situation along the highway. Traditional methods of traffic estimation utilizes these CCTV camera images for vehicle counting [44] and base front [39] estimation. Although, these techniques are highly problematic and erroneous in such images because of their highly noisy nature and decreased ability to isolate vehicle characteristics. Along with low quality CCTV cameras, the process suffer from three major issues, a) low camera resolution resulting in highly noisy images, b) traffic camera's limited field of view and c) light illumination from multiple reflecting sources distorting vehicle classification capabilities.

The detection mechanism is divided into two parts, a day time and a night time estimation methodology. Both mechanisms are different due to the high environmental differences, which results into two different image processing techniques. Apart from the environmental differences, vehicle's headlight and billboard illumination adds considerable noise to the image making vehicle counting difficult.

4.1 Day Time Congestion Detection

During the daytime, the underlying intuition is that when there is no traffic on the road, it appears gray in color irrespective of the natural day light. When the road is filled with traffic, the amount of visible gray(empty road) in the picture reduces because of the majority of vehicles attributing a varied level of non gray color.

To perform traffic density estimation, we first use a simple polygon to manually mark the road segment area for the image analysis. For a given traffic camera feed on a road segment, this is a one-time operation that explicitly specifies the region of interest

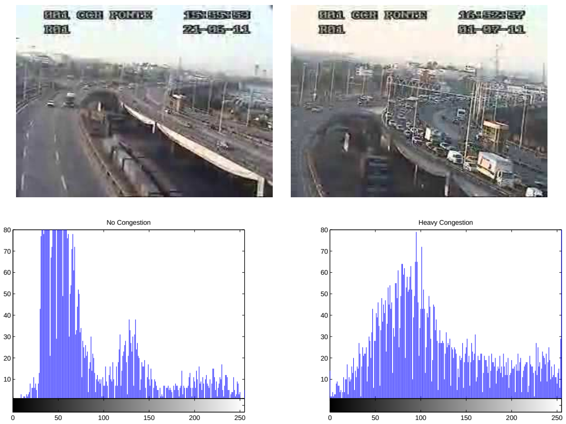

Figure 4: Left: No congestion shot and histogram. Right: Heavy congestion shot and histogram.

Figure 5: Different Threshold levels (a) Original Image, (b) Threshold Level(0.5), (c) Threshold Level (0.7), (d) Threshold Level (0.8)

for the analysis. Then, we convert the picture into an 8-bit gray-scale and analyze the pixels within the marked segment area. For each value (0-255), we plot a histogram for the number of pixels that have each of the 256 different gray-scale values. We have verified that the gray of roads lies in the 135-165 range. Intuitively and backed by the analysis, if an histogram is constructed for the varying levels of gray in the picture, depending on the level of congestion of the road, a histogram would be observed to have a smooth gray level area as compared to a high peak expected in an empty road. With increasing traffic, the peaks at 135-165 begins to reduce and the drop-off at either side is more gradual. By examining these histograms, we can easily estimate the traffic density on the roads. Fig.5 shows snapshots from a traffic feed (along with the corresponding histogram) in Rio de Janeiro (Brazil) The image on the left shows no congestion, and we observe that the corresponding histogram shows peaks in the road gray areas. Similarly, the figure on the right shows a congested road and the corresponding histogram. Observe that the histogram is more evenly spread out, and does not *peak* in the gray areas as much as the case with low congestion.

4.2 Night Time Congestion Detection

Night time congestion detection is a harder problem because of multiple extraneous factors. Absence of light eliminates typical vehicle feature estimation techniques. The next contender for vehicle identification becomes headlight counting, which suffers from light reflection/refraction and alternate light sources such as billboards and traffic signal lamps. Here, we present a summary of our night time vehicle identification technique explained in [38]. The density estimation algorithm estimates the white pixel distribution in the image. We reduce the effects of reflected lightning from our thresholding process which considerably reduces the amount of false light present in the image due to the different intensities of light source and the reflected/refracted light. Fig. 5 shows four images at different thresholding levels and the successive extraneous light reduction in a noisy image.

Since successive thresholding levels affects the image noisiness in a progressive manner, we thresholded multiple images to balance characteristics loss and identify a suitable thresholding level. We found that a thresholding level of 0.8 is an ideal thresholding level for our traffic image dataset.. The thresholding process is followed by a gradient white light estimation across the link length for calculating the traffic density.

Similar to the day time estimation algorithm, the road segment is marked which in our scenario is typically along the middle of the image. The algorithm then calculates the amount of white light in the image, reading a pixel line and registering the pixel measure towards the total white light in a weighted fashion. The weighted factor is required as the observer goes towards the far point of view. Light from multiple vehicles becomes difficult to distinguish and thus a same size segment contains a different number of vehicles as compared to the near point of view. The traffic density in night time is given by:

$$\text{Density} = \sum_i count(i) \frac{H}{H - (P_i/P_\triangle)h_\triangle}$$

where i is the ith pixel line and count(i) represents the number of white pixels in that pixel line. H denotes the actual height of the camera, P_i and $P_\triangle$ represents the projection of the ith pixel line and the last pixel line on the camera approximately. $h_\triangle$ represents the observed height of complete road length in the image and is given by

$$\frac{X_{max}}{X_{max} + d} = \frac{h_\triangle}{H}$$

where X_{max} represents the farthest visible point on the road segment and d represents the nearest visible point of the road segment measured relative to the position of the camera.

4.3 Density mapping function

The final vehicle estimation is done by a simple density mapping function which is used with the help of a semi supervised machine learning algorithm. For each road segment and specific camera feed, we manually estimate the vehicular density for several day-time and night-time images. These density estimates provide the known data for our learning algorithm. Hence, for every road segment, we have manually calculated vehicular density for a very small number of images and the graded density measure analyzed from the image processing algorithm. The unknown data points are analyzed using the known data points by utilizing the Shepard's method of Inverse Distance Weighing [15]. Note that the mapping function differs for night time and day time images. We have a simple background filter function to distinguish between day time and night time images. Given a previously unseen image, we first estimate the graded density measure from the image processing algorithm and then use the manual data to analyze the graded traffic density. We then compute the final vehicular density as a weighted average of the vehicular densities with help from the manually classified images.

5. EVIDENCE OF CONGESTION COLLAPSE

Numerous sources [32, 2, 7, 46] have reported that traffic congestion is a serious problem in many cities in the developing world, leading to billions of dollars in losses annually. To understand the prevalence of congestion collapse, we have analyzed several days worth of round-the-clock traffic feeds from several locations.

The traffic feeds used in this evaluation primarily consisted of CCTV camera feeds. Quite often, video camera feeds consists of an multi-camera stream where feeds from multiple cameras are displayed cyclically with a known time period. Since we base our work solely using camera images, we convert the video feeds to images and aggregate them per camera in an automated manner. The process is easy to perform and can be done in real-time, taking an insignificant amount of time per image. The static images now obtained from the video feeds are fed to the evaluator which utilizes the configured semantics and performs day/night time estimation to analyze the vehicle density estimates.

The sources from which traffic data was collected from were: **Rio de Janeiro, Brazil:** Rio-Niteroi bridge [22, 4], the junction of Av pres Vargas and Av Rio Branco, Camerino, Rd Santana and Rd Frei Caneca.

Mombasa, Kenya: Moi Ave (TSS Bldg), Kengeleni Junction, and Sabasaba Traffic Lights [16].

Nairobi, Kenya: Pushorttam Place (Museum Hill), Barclays Plaza (Uhuru Highway/Kenyatta Ave Rndbt), Ukulima House (Haile Selassie/Upperhill Road Rndbt), National Bank Building (Harambee Avenue), National Bank Building (Railways Roundabout), Nation Centre (Kenyatta Ave/Kimathi Street), Heidelberg Building (Mombasa Road), and a few others [16].

In total, we collected traffic image feeds from all three of the above-mentioned places for a total of 80 hrs during the month of July 2011. Different road segments were identified to exhibit congestion on different timings. A bird's eye view of the source image set displays high congestion in Brazil region during evening which continues to night primarily near 4:30PM to 8:30 PM. On the other hand, traffic in Kenya was observed to be highly erratic and bursty starting from 10AM to ending at 2PM. The evening time traffic was relatively non congested for the Kenyan region.

These feeds show us that congestion collapse is a big problem that occurs on a daily basis. Furthermore, congestion collapse lasts for elongated periods of time (sometimes, spanning over several hours) over long highway roads. In this section, we use camera feeds from two different locations on the famous Rio-Niteroi bridge (Brazil) to illustrate the problem of congestion collapse. This massive 8-lane bridge is over 13 kilometers long, and connects the two cities across the Guanabara Bay. A picture of this impressive bridge is shown in Fig. 6.

Fig. 7 shows pictures from location 1 on the bridge. The first picture in this set was taken at 5:15pm, and congestion sets in barely 5 minutes later (as illustrated in Fig. 1). The next five pictures are taken over a 2-hour period, and we observe that the congestion remains until 7:35pm. This illustrates the fact that once congestion sets in, the operational capacity of the road reduces, thereby leading to long periods of congested traffic. The erratic behavior is observed on a daily basis throughout the analysis.

Fig. 8 shows pictures from a traffic feed from a different location on the bridge. The first picture in this set was taken at 5:05pm, and

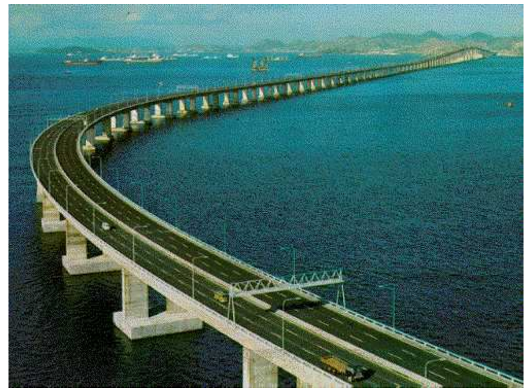

Figure 6: The famous Rio-Niteroi bridge in Brazil across the Guanabra Bay.

Figure 7: Traffic feed from the Rio-Niteroi bridge in Brazil shows shots from a 2-hour long traffic jam (consider the oncoming lane only). Traffic congestion sets in barely 5 minutes after the first picture was taken, as illustrated in Fig. 1.

Figure 8: Traffic feed from a different location on the Rio-Niteroi bridge shows shots from a traffic jam, that lasts for about an hour.

shows an already congested road. The next five pictures are taken over a 45 minute period, and we observe that the congestion remains until 6:00pm. This example also illustrates the fact that once congestion sets in, the operational capacity of the road reduces, thereby leading to long periods of congested traffic. Fig. 9 shows the congestion for a tollbooth where a smooth traffic input leads to a heavily congested output. Within a span of 30 minutes we see a very high congestion build up. The example verifies that even with a controlled flow input, congestion can build up in a relatively short time.

From our traffic feeds in Mombasa and Nairobi, we have observed similar congestion problems that persist over long durations of time. In summary, we conclude that unless the resources of infrastructure are properly managed, congestion will remain a long-term problem.

6. LOCAL DECONGESTION PROTOCOL

In this section, we build on §3, and design a simple protocol that can be used to decongest a small network of links. While the main goal is to demonstrate the fact that intelligent flow control of traffic can mitigate congestion in localized settings, it can also be extended to a larger network of roads. We motivate and describe the protocol through two examples: a) a 2:1 merge, and b) a roundabout which acts as a meeting point for four roads.

6.1 2:1 Merge

We re-visit § 3.2 that introduced the 2:1 merge junction. Except in rare cases, merges between roads follow the free flow model, where there is no throttling of the input rate of traffic. However we have seen that this model easily leads to congestion collapse.

To overcome congestion in a 2:1 merge, it is simple to understand that we need to throttle the amount of traffic entering it. From

Figure 9: Tollboth congestion built up in a span of 30 mins.

Fig. 3, we can see that our goal is to decrease (or, stop) the incoming traffic (through links L and H_{bef}) when congestion takes place in link H_{aft}.

To accomplish this goal, we first need to monitor the traffic density on H_{aft}; we can use the techniques described in § 4 for this purpose. We also place two *emergency signals* on L and H_{bef} a little distance before the actual merge point. When there is no congestion on H_{aft}, these signals are green, thereby allowing the free flow and merging of traffic. As soon as the traffic density $B_l(H_{aft})$ begins to approach $B_l^*(H_{aft})$, we need to throttle down the incoming traffic.

The signals at L and H_{bef} therefore change to red for certain durations to allow the density $B_l(H_{aft})$ to reduce. The traffic density at an epoch $t+1$ is related to the that at epoch of time t by the following simple equation:

$$B_l(t+1) = B_l(t) + input - output$$

. This equation is used to determine how much traffic can enter in an epoch from both L and H_{bef}; which determines the amount of time that the signals can be kept green. In order to calculate how to divide the green time between the signals, a simple (yet, effective) method is to divide the total permissible green time amongst them in a ratio that is proportional to their traffic densities (which in turn, are monitored by sensors). This mechanism guarantees that the link H_{aft} will never go into congestion collapse.

This approach can be simplified as follows: Consider the composite region of L and H_{bef} that lie after their emergency signals, combined with a small portion of H_{aft} that lies after the merge point. This region behaves like a junction, and has its own traffic curve. By using just one camera, we can estimate the traffic density in the entire junction, and use this composite traffic curve to perform traffic flow control.

This approach can easily be generalized to an n:1 junction in the same manner. We study the efficacy of this protocol in § 7, where we show that congestion collapse can be easily prevented.

6.2 Four-way Roundabout

Similar in spirit to § 6.1, we explain the decongestion of a four-way roundabout. The roundabout has short segments on its input/output links as a composite junction j, with its own traffic curve. Each of the links that leads into the roundabout has an emergency signal that turns red as a reaction to congestion in the roundabout. When the traffic density of the junction $B_l(j)$ is lower than $B_l^*(j) - \epsilon$, all these signals are green.

When the junction nears its congestion threshold density $B_l^*(j)$, the signals will have a reduced green time, determined by the actual density $B_l(j)$. This green time is divided amongst the input links in a manner proportional to their traffic densities. As before, this approach can be generalized to any junction with n input and output links.

6.3 Localized Congestion Areas

The mechanism described above for the 2:1 merge and roundabout cases can be generalized for local congestion areas. Consider a localized congestion area which has a small network of roads and a set of N input/output traffic signal points which dictate the input and output flow out of this localized area. Based on free flow traffic theory [43], any free flow road segment can be associated with an approximate traffic curve as described in earlier examples. Given that the localized area is a high congestion area, we can assume that most road segments are used at high capacity even in the presence of traffic signals. Hence, there is constant flow across different directions within the localized region. In our local de-congestion protocol, we explicitly model a localized congestion area with an approximate traffic curve with a tipping point as specified by the traffic curve. The exact parameters of the traffic curves and the tipping point can be generated using simulation based analysis of the road network topology for different arrival patterns.

Consider a local congestion area A with a traffic curve and a tipping point Δ and a set of N input /output signals $T_1, \ldots T_N$. Our local decongestion protocol works as follows. Consider two small safety thresholds $\epsilon_1 > \epsilon_2 > 0$ with a small separation between two values. Let $\delta(A, t)$ represent the traffic density in the congestion area A at time t. Our decongestion protocol uses CCTV camera feeds at each of the input and output points to estimate the input flow $X_i(t)$ and output flow $Y_i(t)$ at each signal i (both are measured in terms of traffic density). Hence, the system measures the net flow into the congestion area across all the signals at time t as $\sum_i X_i(t) - \sum_i Y_i(t)$ and normalizes the net flow in terms of traffic density change within the area. Using this measure, the protocol constantly measures $\delta(A, t)$ within the traffic area. If the local density is less than $\Delta - \epsilon_1$, then the local decongestion protocol does not alter traffic signal behavior. The local decongestion protocol triggers when

$$\delta(A, t) > \Delta - \epsilon_2$$

When this event happens, the traffic density is close to the tipping point threshold. At this juncture, the local decongestion protocol provides feedback to the individual signals to increase the "red" signal time and reduce the input flow. The traffic input rate at each signal is kept as proportional to the estimated queue size based on the image feeds from the individual signals. The protocol continuously provides feedback to increase the "red" signal time until the density drops below $\Delta - \epsilon_1$. The two safety thresholds are used to emulate a simple hysteresis behavior. In practice, ϵ_1 and ϵ_2 are very small constants.

7. EVALUATION

In this section, we provide an evaluation of our protocol, to demonstrate the efficacy of the decongestion protocol in alleviating congestion collapse in road traffic networks. The specific sample topologies we consider are: a) n:1 merge and b) four-way roundabout. We evaluate our protocol across these topologies, and show how our protocol avoids congestion collapse and provides considerable enhancements to the operational capacity.

7.1 Methodology

The first step in performing the simulation is identifying the essential parameters, a list of which is given below:

1. The number of links n in the network. Each link l has a traffic curve that is defined by two values: B_l^* and C_l^*. The minimum delay d_{min} a vehicle will face in the link is governed by the equation: $B_l^* = d_{min} \times C_l^*$. Therefore by specifying d_{min} and C_l^*, we define all the characteristics of the traffic curve. The delay d that a vehicle will face in the link is calculated using d_{min} and the current traffic density B_l. Furthermore, the rest of the traffic curve for the link can be approximated from these values.

2. The number of junctions/merges in the network. Each junction/merge is identified by which input links flow into it, and which output links flow out of it. This determines the topology of the localized network.

3. The number of sources (vehicle generation points) in the network. Each source also defines which link it will send all its traffic into.

4. The number of sinks (end-points of vehicle journeys) in the network. Each sink also defines which link it receives all its vehicles from.

5. Vehicle routes are determined when a vehicle is generated by a source. Each source is configured with a (possibly large) set of pre-determined routes that a vehicle generated by it can take. The simulator verifies that these routes are legal (allowable by the topology) before starting the simulation, and then randomly chooses one of these routes for every vehicle upon generation.

6. Vehicle generation rates (burst rates) can also be configured for each of the sources. These rates are set over variable length epochs of time.

7. The exit rate of free-flow links is determined by its traffic curve and current density. Links feeding into a junction/merge can emit vehicles at their maximum rate C_l^*.

Once the various parameters are identified, a parameter file for the topology is created. The simulator uses this parameter file and simulates the functioning of the road network. We simulate each topology for a period of 40 minutes. In the results presented here, each traffic source generates vehicles uniformly within epochs that last 10 minutes each; the burst rate can vary across epochs.

The simulator records the time at which a vehicle was generated by the source, and the time it was absorbed by the sink. It can therefore calculate the travel time, along with the throughput (average number of vehicles that reach their destination) at any point of time. In our graphs, we plot the throughput on the Y-axis, and time (in seconds) on the X-axis. The throughput at any second is the total number of vehicles that have reached their respective destinations in the 60 second period centered around that second.

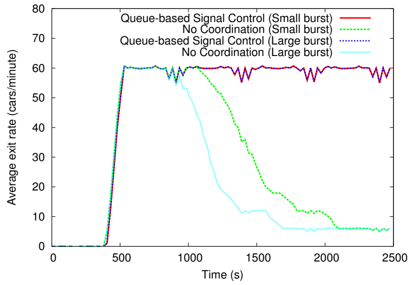

Figure 10: $2:1$ **Merge with** $d = 300s$**. Small bursts can lead to collapse, which can be prevented using intelligent signaling.**

Each graph plots two scenarios: a) when no *signaling* (or, local de-congestion protocol) is used (free-flow model), and b) our protocol (§ 6) is used.

7.2 n:1 Merge

The evaluation was conducted on this topology to examine the effectiveness of the proposed signaling system in simple scenarios in which merging of traffic across multiple links to a single point of confluence. In this study, we repeat the experiments for $n = 2, 4$.

For the n:1 merge simulations, we set the the n input links to have $d = 160s$ and $C_l^* = 1.0$ cars per second. The output link has $C_l^* = 1.0$ cars per second. We repeat the simulation for the output link having $d = 300s$ and $d = 450s$. There is a source at each of the input links, and each source generates traffic at a constant rate during the 40 minutes of the experiment. In addition, each source inserts an additional *burst* between $t = 10min$ and $t = 20min$. We repeat the simulation for two different burst values as described.

7.2.1 2:1 Merge

Each source generates traffic at a constant rate of 30 cars per minute. The additional burst is either 10 cars per minute (large burst) or 5 cars per minute (small burst). Fig. 10 plots the output rate when the destination link has $d = 300s$. Congestion collapse occurs as soon as the output link density goes above its B_l^* value, which takes place about 10 minutes into the simulation. The output rate continues to decay as the buffer of the output link continues to operate in the congestion region. However if signaling is used, then the flow into the output link is controlled by metering the cars flowing in from the two input links. As a result, the output link continues to operate at its maximum capacity of 60 cars per minute. Similarly, Fig.11 plots the output rate when the destination link has $d = 450s$. The behavior is very similar to when $d = 300s$, with the difference being that when $d = 450s$, congestion sets in after a larger delay, because of the larger buffer on the destination link.

7.2.2 4:1 Merge

Each source generates traffic at a constant rate of 15 cars per minute. The additional burst is either 10 cars per minute (large burst) or 3 cars per minute (small burst). Fig. 12 and 13 plot the output rate with the destination link has $d = 300s$ and $d = 450s$ respectively. We observe that in both cases, congestion sets in as soon as the additional burst is issued by the sources, and it lasts a long time. Smart signaling can keep the buffer sizes below the breakdown region, thereby averting congestion.

7.3 Four-way Roundabout

The roundabout topology can be simplified as follows: There are 8 links $L_1 \cdots L_8$, with four of them flowing in to the roundabout,

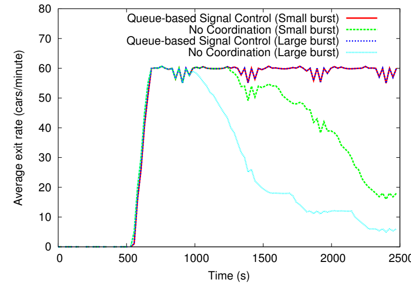

Figure 11: $2:1$ **Merge with** $d = 450s$**. Small bursts lead to collapse, albeit slightly delayed (when compared to** $d = 300s$**) because of larger buffer sizes of the destination road. Signaling prevents congestion collapse.**

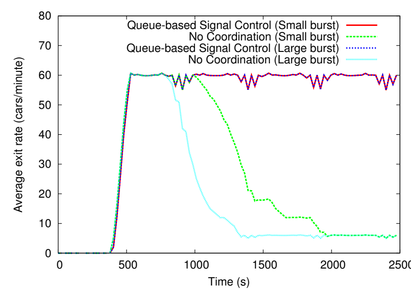

Figure 12: $4:1$ **Merge with** $d = 300s$**. Small bursts can lead to collapse, which can be prevented using intelligent signaling.**

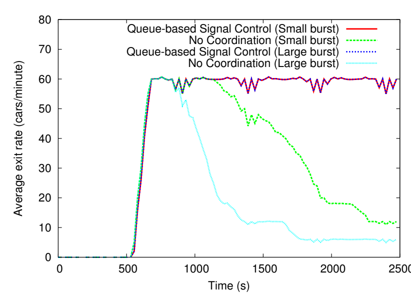

Figure 13: $4:1$ **Merge with** $d = 450s$**. Small bursts lead to collapse, albeit slightly delayed (when compared to** $d = 300s$**) because of larger buffer sizes of the destination road. Signaling prevents congestion collapse.**

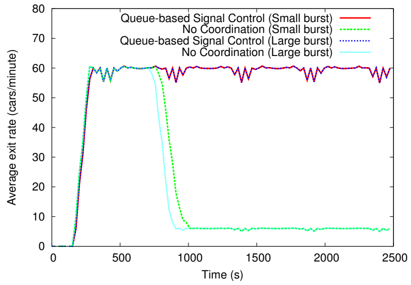

Figure 14: Roundabout with $d = 60s$: The small buffer size of the roundabout leads to congestion quickly taking place, which can be prevented using signaling.

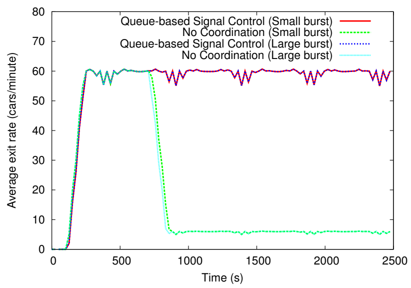

Figure 15: Roundabout with $d = 20s$: The extremely small buffer size of the roundabout leads to congestion immediately taking place, which can be prevented using signaling.

and the other four flowing out of it. These links have identical traffic curves, with $d = 160s$ and C_l^* set to 1.0 cars per second. The roundabout is associated with a traffic curve, with parameters $C_l^* = 1.0$ cars per second, and the experiment is repeated for $d = 60s$ and $d = 20s$. The four incoming links are each served by a source, while the four outgoing links each flow into a sink. Each source generates traffic at the rate of 15 cars per minute during the entire experiment. Each source generates an additional burst from $t = 10min$ to $t = 20min$ of 10 cars per minute (large burst) or 3 cars per minute (small burst).

From Fig. 14 and 15 we observe that if signaling is not used, the roundabout gets congested very quickly. This congestion collapse lasts till the end of the simulation. However if we use smart signaling to control the flow of traffic from the four input links into the roundabout, we can keep the roundabout operating at its optimal capacity, thereby avoiding congestion collapse. We verified that this behavior is repeated with different traffic burst rates, and different traffic curves for the links. In particular, we observe that when the roundabout has a smaller buffer capacity ($d = 20s$, as illustrated in Fig.15), even a very small burst over a very small period of time is enough to congest the roundabout.

8. RELATED WORK

The problem of traffic congestion has been prevalent in both developing and developed countries. Variety of solutions have been developed in the previous decade [23, 19, 25, 27], but as mentioned in § 2, developing countries suffer from an additional set of constraints hampering these predefined solutions making the problem tougher. Congestion prevention and congestion control are the two approaches to solve the traffic congestion problem. Congestion prevention focuses on reducing the number of incoming vehicles in the road traffic networks. Numerous ways have been devised by various government authorities like promoting car-pooling systems [36], congestion pricing or time variable toll mechanisms [33, 35, 34] and car plate quotas [7]. Congestion control mechanisms includes traffic engineering and monitoring. The available real-time information from deployed road sensors is leveraged and a predictive analysis is applied to propose near future traffic patterns and develop a situational solution to tackle the current traffic. Nowadays real-time traffic information is collected from various sources like traffic cameras, road sensors and even cellphone providers [29, 18, 13]. Advance GPS systems mitigate this problem by finding less congested routes [28, 10]. Various mechanisms like variable speeding, ramp metering and lane specific signaling are applied on available real-time information to manage traffic congestion. [41] proposes the usage of histogram based density discovery scheme for road connectivity which is leveraged for LOURVE [40]; LOURVE focuses on global route optimal scheme to calculate best paths on its defined overlay network. [42] develops a new algorithm FlowScan, to cluster road segments instead of clustering the moving traffic to identify congested traffic routes.

Texas Transportation Institute (TTI) [26] has developed several applications that are widely used in local, state and federal levels for controlling the signal timing information [20]. McTrans [17] project at University of Florida provides a host of applications related to road traffic management. HCS+ [11] and Traffic Network Study Tool [30] provides signal timing optimization based on a variety of objective functions. Contram [8] is another software which provides real time traffic monitoring and optimized real time traffic routes. It is currently deployed in places like Stockholm, Kent and other large cities. The Sensor Project [24] enables efficient data collection so that traffic management can be done in a better way, by the use of sensors to collect the data. There are also applications which monitor existing real time traffic and predict traffic models which can prevent traffic congestion. Applications like IBM Traffic prediction tool [12] and the combination of Caliper Products [6](Transmodeller and TransCAD) are used to simulate and predict traffic models.

Use of third party mediums to disseminate traffic information is being actively pursued. Danilo [45] explores the idea of cellular networks to convey information to users of information. Akinori et al., [37] proposes creation of well formed maps which could be used by mobile traffic information services. However, in our case, we intend to create monitoring and signaling stations which can take decisions on their own without user intervention and hence, regulate traffic.

9. CONCLUSION AND FUTURE WORK

Road traffic congestion is a central problem in most developing regions. Most urban areas have poorly managed traffic networks with several traffic hot-spots or potential congestion areas. In this paper, we study the problem of road traffic congestion in high congestion hot-spots in developing regions. We first present a simple image processing algorithm to estimate traffic density at a hot-spot using CCTV camera feeds. Based on analysis of traffic images from live traffic feeds, we show evidence of congestion collapse which last for elongated time periods. Based on the free-flow *traffic curve* behavior of links, critical road segments when exposed to short bursts in traffic can result in the specific segments operating at low-capacity levels for long time periods. To partially alleviate this problem for small congestion areas such as traffic hot-spots, we develop a local de-congestion protocol that controls the flow of traffic into near-congested regions, thereby preventing collapse caused by short bursts of traffic. Our hope is that localized de-congestion mechanisms are potentially easier to deploy in real-world settings and can enhance the traffic flow at critical hot-spots in road traffic networks. We believe that this represents only a first step in the development of low-cost, deployable strategies for alleviating congestion in developing regions.

The future work lies towards deploying a real time proof of concept to analyze instantaneous traffic density. The paper discussed a means to detect and curb congestion in a localized setting. Although, the solution is feasible to affect local congestion, it is still not able to curb the congestion extending for miles due to the localized focus of the approach. The analysis can thus be improved with multiple sequential cameras along a highway which in addition to localized congestion control analyzes the congestion buildup from the starting point to the ending point. With the aggregate image data, the congestion control strategy can make global decisions and affect congestion control on a reasonably sized scale.

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