Different Sensing Modalities for Traffic Monitoring in Developing Regions

A synopsis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

by

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20th January, 2013
Introduction And Motivation

Road traffic congestion is an acknowledged problem worldwide. Long travel delays, unpredictable travel times, wastage of fuel, environmental pollution etc. are some of the direct issues posed by unprecedented and ever growing congestion levels in the cities. A developing country like India, which is the second most populous country in the world, and a fast growing economy, is seeing terrible road congestion problems in its cities.

Intelligent Transport Systems (ITS) do better management of traffic flows and make commuters more informed about traffic and road status. ITS in India, however, cannot be a mere replication of deployed and tested ITS in the developed countries. The typical lane-based orderly traffic seen in developed countries is shown in Fig. 1. Traffic in developing countries like India, is however, very different in its form and characteristics, as can be seen in Fig. 2. Two-wheeler motorbikes, three-wheeler auto-rickshaws, four-wheeler cars and heavy vehicles likes buses and trucks, ply together on the same road, intermingled with each other, without any lane discipline. Such non-lane based disorderly traffic needs the existing traffic sensing techniques like [1, 9, 5, 6, 3] to be adapted to the Indian scenario, before they can be used.

This thesis investigates the problem of monitoring road traffic that does not follow lanes. It proposes and builds two novel traffic sensing systems using acoustic and radio frequency (RF) sensors. In addition, it also examines the well studied methods of traffic sensing based on computer vision, and adapts the methods to non-laned traffic videos.
The implemented systems are deployed and evaluated in real on-road traffic, in the Indian cities of Mumbai and Bengaluru.

For each of the three sensing modalities – acoustic, RF and video, examined in this thesis in the context of chaotic non-laned traffic sensing, there are typically three research questions explored in depth. The first question is the design of the sensing algorithm, where we carefully design and evaluate empirical heuristics choosing what to sense and how long to sense. The what to sense question decides the acoustic, RF and video features that best characterize the road traffic state. The how long to sense question balances the high frequency noise in sensing windows that are too small versus change in the traffic state to be decided or non-responsiveness to the application being handled, if the sensing window is too long. This is the empirical heuristic design component of the thesis.

The second research question is the design and implementation of embedded platforms and wireless protocols to handle certain applications by building upon the three sensing modalities. The applications are per minute congestion monitoring using acoustic sensors, real-time measurement of traffic queue lengths using RF sensor arrays and relating traffic parameters like speed, density and flow using video sensors. This research question involves careful systems design and implementation and deployment based evaluation of the application accuracies. This is the system building component of the thesis.

The third research question is relevant for the first two methods of acoustic and RF sensing, which indirectly infer traffic conditions by correlating sound or RF signatures with traffic states. This is unlike video, where traffic conditions are directly observed and measured. In the indirect methods, a component of labeling the acoustic or RF sensor data with traffic states is involved, in the training phase of the traffic state classification models. Thus the question of road specific model training, the suitability of unsupervised classification models and the manual labeling overhead involved in supervised classification, have been explored by large scale deployment data collected in collaboration with city traffic authorities. This is the applied machine learning component of the thesis.
Horn-0k-Please: Acoustic Sensing Based Road Congestion Monitoring

Noise in Indian roads has a unique characteristic, namely *abundance of vehicular honks*. They are tightly knit with the driving “protocol”, so much so that honking is considered an aspect of “safe” driving. We seek to develop a vehicle speed estimation technique, using roadside acoustic sensors that record vehicular honks. Based on the Doppler shift observed in the measured frequencies of the honks, it is possible to estimate the speed with which the honking vehicle is moving. Such speed estimates and also non-speed based acoustic metrics, can be used as indicators of traffic situations on the road.

**Speed estimation using Doppler shift:** If source of sound moves with speed $v_s$, receiver of sound is stationary, emitted frequency of sound is $f_0$ and speed of sound is $v$, then when source moving away from the receiver, frequency observed at receiver is,

$$f_1 = \frac{v}{v + v_s} f_0$$

when source moving towards the receiver, frequency observed at receiver is,

$$f_2 = \frac{v}{v - v_s} f_0$$

If $f_0$ is known, $v_s$ can be estimated easily from equations 1 and 2. But it is not easy to guess $f_0$ as different honks have different base frequencies. In absence of $f_0$, we thus need to use an alternate arrangement using two sound receivers, as shown in Fig.3. When a moving vehicle blows honk in between the two receivers, it is approaching one receiver and receding from the other. Substituting value of $f_0$ from equation 1 in equation 2, we get following equation,

$$v_s = \frac{(f_2 - f_1)}{(f_1 + f_2)} v$$

Estimation of $v_s$ is thus a three step process: (1) **detection of honk** from the recording at each of the two sensors in presence of background noise, (2) **Matching honks** across recordings in two sensors to identify the same honks recorded in both and (3) **Extracting frequencies** $f_1$ and $f_2$ in Equation 3 from each honk pair, matched
as the same across the two sensors. Using the $f_1, f_2$ obtained through the above three step process and taking speed of sound ($v$) = 340 m/sec, we can estimate $v_s$ applying Equation [3].

![Figure 3: Acoustic Sensing Setup](image)

Careful design of heuristics for these three steps, by continuous evaluations on real road noise recordings, gives average error of less than 5 Km/hr and relative error of less than 10% of our speed estimates, compared against speedometer based ground truth speed values. These heuristic design and evaluations have been done using N79 phones as noise recorders and offline processing of the recordings.

**Metrics to classify traffic states:** Using these speed estimates, we observe the speed distributions of 18 hours of road data, collected from two Mumbai roads in Hiranandani, abbreviated as *Hira*, and Adi Shankaracharya Marg, abbreviated as *Adi*, in Nov 2009. Half the road data belongs to the free-flow traffic state, where drivers can drive in the speed they want, limited by the speed limit. The other half of the data belongs to the congested state, where drivers have to slow down, brake or stand altogether. The speed distributions over 10 minutes show metrics like (1) $70^{th}$ percentile speed and (2) percentile speed less than 10 Km/hr, characterize the underlying traffic state of free-flow vs. congestion. Also some non speed based acoustic metrics like (3) number of honks, (4) duration of honks and (5) noise level on the road, seem to reflect the traffic state. We test these metric values for non-parametric statistical divergence tests like Kolmogorov-Smirnov and Mann-Whitney, and get very low p-values (given in Fig. [4]) for the first four metrics. Such low p-values indicate that these four metrics can differentiate the two traffic classes of congestion vs.
free-flow accurately.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Mann-Whitney U test</th>
<th>Kolmogorov-Smirnov test</th>
</tr>
</thead>
<tbody>
<tr>
<td>70th perc. Speed</td>
<td>2.0E-006</td>
<td>7.48E-007</td>
</tr>
<tr>
<td>Percentile of speeds &lt; 10 Kmph</td>
<td>1.0E-005</td>
<td>2.29E-004</td>
</tr>
<tr>
<td>Num. Honks</td>
<td>5.6E-013</td>
<td>7.33E-014</td>
</tr>
<tr>
<td>Honk duration</td>
<td>2.69E-014</td>
<td>2.90E-014</td>
</tr>
<tr>
<td>Noise</td>
<td>2.1E-013</td>
<td>0.013</td>
</tr>
</tbody>
</table>

Figure 4: p-values for non-parametric statistical divergence tests

A proof-of-concept experiment on whether our metrics can detect the onset of congestion, is conducted between 6pm-8pm, on 4th Dec, 2009, on Adi. Traffic is initially free flowing. It starts becoming congested from about 6.35pm. Heavy congestion set in by 7.10pm. The values of the four metrics (1) 70th percentile speed, (2) Percentile of speeds < 10 Kmph, (3) Number of honks and (4) Duration of honks are plotted in Fig. 5 and Fig. 6 respectively.

According to each metric, we start in free-flow state, and finally move to congestion in the 2-hours, thereby showing the efficacy of our metrics in detecting congestion.

Prototype hardware: As pointed out earlier, the design of the heuristics for speed estimation and the proof of concept experiments to detect congestion, have been done using N79 phones for recording and offline processing of the recorded sound files. We
next investigate the feasibility of such acoustic signal processing in near real-time, on in-situ embedded platforms, to be used in real deployments. We design the hardware prototypes for Recorder 1 (R1) and Recorder 2 (R2), as described in Fig. 3, according to the schematic presented in Fig. 7. R1 (shown in Fig. 8), has a microphone and an FM transmitter. It samples noise using the microphone and sends the sampled noise to R2 over FM. As empirically tested, FM incurs zero propagation delay and thus eliminates the need to time synchronize R1 and R2. Also the use of licensed FM is permissible over the short 30 m distance between R1 and R2, requiring low power transmission.

R2 (shown in Fig. 9), has an FM receiver to receive the noise from R1 and also a second microphone to sample noise at its own location. These two noise feeds are sent over two mono input connectors into the stereo input of a TI C5505 ezdsp board. The DSP is programmed to sample these noise inputs, perform background subtraction outside the honking frequency range of 2-4 KHz, estimate speed after detecting and matching honks according to the heuristics designed earlier and store these speed samples in a Spansion SPI flash. R2 has a SIM300 GPRS modem, so that the speed samples can be sent to a remote server, every alternate minute, over GPRS. The unit is enclosed in a water-proof ABS plastic box and powered with 6 Li-ion batteries with 12V output voltage, 3A peak current and 4AH capacity.

**On road deployment:** We deploy the prototype hardware at six locations in Mumbai - Bhandup, Vikhroli, Gandhinagar, Chandivali, Ghatkopar and Powai (Hiranandani), from 22nd to 27th Nov, 2010, for 2-3 hours on road, along with manually observing the traffic state, one day at each deployment location. The prototype sends the number and duration of honks and the speed values estimated over a minute, to a remote server in
the next minute. Sample plots for the two metrics of $70^{th}$ percentile speed and duration of honks for Gandhinagar between 6-8 pm are shown in Fig. 10 and Fig. 11 respectively, which show the gradual change from free-flow to congested state. The green colored bars denote free-flow condition according to manually observed ground truth and the red colored bars denote congestion. Thus per minute congestion monitoring using acoustic sensing is technically feasible using our methods and prototype.

![Sample plots for the two metrics of 70th percentile speed and duration of honks for Gandhinagar between 6-8 pm.](image)

**Figure 10:** $70^{th}$ percentile speeds at Gandhinagar

**Figure 11:** Duration of honks at Gandhinagar

**Model training and other limitations:** We, however, observe a difference in the correspondence levels between the metrics and the traffic states, at different locations. For example, Vikhroli has a lot of honks even in free-flow, as pedestrians frequent this location. Number and duration of honks are thus not good indicators of traffic congestion at Vikhroli. Supervised training of classification models for each location will take care of such issues, assigning low weights to unimportant metrics. Thus training our system at different locations will have manual overhead.

Some other shortcomings of our acoustic sensing system are (1) dependence on driver behavior to get honk samples. We have anecdotal evidence of drivers sometimes not blowing honks while waiting at traffic signals, whereby our system fails, (2) slow output rate of the system requiring a minute or more to accumulate enough honks and (3) coarse binary traffic classification into congestion and free-flow instead of finer levels.

However, the solution is novel and pioneers acoustic sensing for traffic monitoring, does not have lane-based orderly traffic assumptions, does not disrupt traffic flow during installation and maintenance and is cheap at $160 per prototype.
Kyun Queue: RF Sensing Based Traffic Queue Monitoring

After discussing acoustic sensing in the previous section, we now present our second sensing modality using wireless radios across roads. It is well known in the wireless networking domain, that characteristics of wireless links like 802.11 and 802.15.4 are affected in the absence of LOS [19]. Obstacles cause reflection, absorption and scattering of the RF signal, degrading the link quality. Researchers have exploited these vagaries of RF links in different kinds of application scenarios, the most common being that for indoor localization [20] [11] [16].

The basic intuition: Based on this Radio Frequency (RF) sensing, we seek to design a traffic sensing system in chaotic road conditions. The basic intuition is as follows. If a wireless transmitter-receiver pair is kept across a road and made to communicate as shown in Fig. 12, the link characteristics, observed at the receiver, should be affected by the vehicles on the road. A similar system exists which uses active infrared (IR) sensors placed across roads [3]. However, IR propagates as a ray, and hence is strictly line of sight (LOS) based. This makes it overly sensitive to even small obstacles. Unlike IR, the 802.11 or 802.15.4 wireless signals follow the spread model of propagation, and hence should suffer less from false positives.

Proof of concept experiment: To verify our intuitions, we create a setup shown in Fig. 12 on Adi Shankaracharya Marg, a road in Mumbai, about 25m wide in each direction. We keep two 802.15.4 compliant Telosb motes across the road, one as transmitter (tx) and the other as receiver (rx), on a line perpendicular to the length of the road. The tx sends 25 packets per second, each having a payload of 100 bytes, at $-25\text{dBm}$ transmit
power. The rx logs the number of packets received and Received Signal Strength Indicator (RSSI) and Link Quality Indicator (LQI) for each received packet. One person stands on the roadside footpath holding the rx and another stands across the road, on the road divider, with the tx, both rx and tx being at a height of about 0.5 m from the ground. These two persons also observe the road to note the ground truth of the traffic situation. We collect 14 logs of 5 minutes each from about 5:30 pm to 7 pm.

Figure 13: CDF of RSSI over 5 minutes

Fig. 13 shows the CDF of RSSI, each of the 14 plots is a CDF calculated over 5 minutes. As seen from the figure, the curves can be classified into three distinct groups – Group1 between 5:37-6:21pm, Group2 between 6:22-6:27pm and Group3 between 6:30-7:05pm. The ground truth of traffic state noted is free-flowing till 6:20pm, slow for about 5 minutes and then heavily congested till the end of the experiment. Thus Group1 corresponds to free-flowing traffic, Group2 to slowly moving traffic, intermediate between free-flowing and congested and Group3 to heavily congested traffic. The high correlation of the CDFs with traffic state is apparent visually. For e.g., the 50th and 70th percentiles of RSSI are around -93dBm in congestion and -78dBm in free-flow.

Choice of features and sensing time window: Other than RSSI, Link Quality Indicator (LQI) and Packet Reception Rate (PRR) also show sensitivity to traffic conditions, but errors increase if such features are added to RSSI features for building classifier model. We also experiment with the sensing time window, during which wireless packets are accumulated and features are extracted from the accumulated packets. Fig. 14 shows how the training errors come down with the increase in sensing time window, as very small
windows suffer from high frequency noise like two heavy vehicles simultaneously crossing the RF sensors in free-flow, momentarily causing the signal to be very bad. 20 seconds of sensing, shown by a vertical line, gives above 90% accuracy. So we use the $20^{th}....90^{th}$ percentiles of RSSI of wireless packets accumulated over 20 seconds, as features in our traffic classification models, which gives above 90% binary classification accuracy on 16 hours of road data, collected over three weeks, from two Mumbai roads.

The Kyun Queue architecture: With this highly accurate and low computation over-

![Figure 15: Queue measurement architecture](image)

head method of traffic classification, we next build an architecture as shown in Fig. 15. Here each sensor pair (T-R) classifies traffic state locally, and the individual decisions are correlated at the controller (C) to know the traffic queue length. From an application perspective, C can tune the traffic signal according to the queues waiting on each incoming lane. Also multiple C units from different road intersections can communicate the queue information to a central server, from where the traffic signals over a city-wide road network, can be controlled co-ordinatedly.

The hardware challenge is to use RF both for (a) sensing between the T-R pairs, requiring the radios to be at low height from the ground to let the vehicles affect the wireless signal and (b) communication between R-R and R-C over long distances like 60 m, if each R is placed on alternate lamp-posts. We use two radios in the R units, one for sensing and the other for communication. The hardware platforms for T, R and C are shown in Fig. 16, 17 and 18 respectively. The software challenge to time synchronize sensors to sense, classify traffic states and communicate co-ordinatedly, is handled by a centralized protocol controlled by C. Interference from Wi-Fi access points has been mitigated by disabling some radio features and using channels 25, 26 outside Wi-Fi range.
Deployment based evaluation: Five pairs of T-R prototypes and one C unit, powered with batteries and packaged in ABS plastic boxes, are deployed on Nov 17, Nov 18 and Nov 19, between 6-9 pm every day on a stretch of Adi Shankaracharya Marg in Mumbai. The measured queue length values by the deployed system is communicated to a remote server from C, over GPRS. An android phone, kept on the roof of an apartment building, takes periodic photographs to provide ground truth for the queue measurements.

<table>
<thead>
<tr>
<th>Date</th>
<th># of detections</th>
<th>% Exact Matches</th>
<th>% Error of 1 unit (about 30m)</th>
<th>% Error of 2 units (about 60m)</th>
<th>% Error of 3 units (about 90m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nov 17</td>
<td>359</td>
<td>74.09</td>
<td>20.05</td>
<td>4.45</td>
<td>1.39</td>
</tr>
<tr>
<td>Nov 18</td>
<td>359</td>
<td>96.37</td>
<td>1.67</td>
<td>1.39</td>
<td>0.56</td>
</tr>
<tr>
<td>Nov 19</td>
<td>353</td>
<td>90.93</td>
<td>7.64</td>
<td>1.97</td>
<td>0</td>
</tr>
<tr>
<td>Overall</td>
<td>1071</td>
<td>87.11</td>
<td>9.8</td>
<td>2.4</td>
<td>0.65</td>
</tr>
</tbody>
</table>

Table 1: Accuracy and error breakups of deployment results

A subset of our deployment results are presented in Table. The accuracy is upto 96% on Nov 18 and Nov 19 and Nov 17 has minimum accuracy: 74%. But on Nov 17, queue buildup and clearing was very rapid, increasing the challenge of deciding queue length by manual observation. So our low accuracy is likely a combined effect of our errors and errors of manual ground truth estimation. For example, the instant the image is taken, the queue might have cleared but it might have been present for most of the 20 seconds of sensing, leading to a false positive. But even on Nov 17, higher errors of 2-3 units, are very low. The above results indicate that, the Kyun Queue system is accurate in estimating traffic queue lengths, and shows good promise for use in applications such as automated traffic signal control.
Road specific classification model training: We also analyze the training overhead of our RF based traffic classification models, through a collaboration with the Bengaluru traffic police, who have video feeds from road intersections coming to a control room (Fig. 19). We deploy our RF sensors at three intersections to collect RF data between March 25 and May 5, 2012, 8 am to 8 pm everyday, and collect the corresponding video ground truth from the traffic police. The three locations are shown in Fig. 20, where AURO is 8 m wide with only light vehicles, JD is 10 m wide with all vehicles and UDI is 25 m wide with all vehicles.

Figure 19: Control room in Bengaluru

Figure 20: AURO, JD, UDI junctions with sensor location marked

Analyzing this significant volume of sensor data, we show that (1) we indeed need different classification models for roads of different widths; but dependence on vehicle types is largely absent, (2) unsupervised classification can lead to poor accuracy, however (3) manual supervision as little as a few minutes per road is sufficient to achieve near-100% classification accuracy.

Conclusions: Thus the RF sensors give above 90% accurate traffic classes with short sensing periods of 20 seconds, combining which from an array of sensors, upto 96% accurate queue measurements can be obtained. Training overhead for these sensors is also low. In terms of accuracy, timeliness and training, these are better than the acoustic sensors. In comparison with video, all computations can be done in-situ and only queue measurements are communicated; while in-situ video processing for non-laned traffic is yet to be solved requiring high-bandwidth video transfer from roads to server at present. In comparison with underground magnetic loops, RF sensors incur lower cost and less installation overhead being road-side sensors. In comparison with GPS sensors, the applications like intersection management that we aim with RF sensors, are orthogonal and complementary to the travel time estimation applications handled by mobile sensors.
**SpeeDen: Computer Vision Based Accurate Speed and Density Measurement in Non-laned Traffic**

The third and final sensing modality that we discuss is video processing. Traffic cameras and computer vision algorithms are the most prevalent method for traffic sensing worldwide [6]. In Indian cities also traffic cameras are being constructed at important road intersections, like the video cameras in Bengaluru which we used for ground truth collection in our RF sensor deployments. In absence of appropriate automated methods, the current traffic control rooms as in Bengaluru, have traffic officials manually observing the video feeds, to detect congestion and other anomalies.

**Prior work:** Automated video processing for non-laned traffic is an active area of research [10, 17, 13]. [10] gives two algorithms to produce a binary classification of traffic density, one algorithm for daylight conditions and the other for night time. The algorithm for daytime uses a histogram of gray-scale images to classify traffic which requires manual training; and ultimately, this algorithm is limited to binary traffic state classification. There has not been an empirical evaluation of the accuracy of the algorithm yet, which leaves uncertainty about its effectiveness in detecting vehicles that match gray-scale color of the road.

Some techniques [8, 12] track vehicle features to calculate vehicle trajectories across frames and have been thoroughly evaluated in lane-based orderly traffic. Similar feature based tracking in non-laned traffic is done by [13]. It uses Haar features to detect vehicles anywhere in a given frame and classifies each vehicle into one of five categories. Searching for Haar features over an entire frame needs 8 core processors to run in real time, 4 GB RAM and a 650 GB hard-drive in both online and offline computation. Also, in high traffic density, vehicle occlusion makes feature matching challenging.

[17] describes a preliminary effort to compute and group motion vectors between consecutive video frames to show position and velocity of vehicle motion. There has not yet been an evaluation comparing the velocity values to ground truth values to evaluate accuracy of the system.
Our density measurement approach: To compute traffic density, we place a colored strip, either painted or taped, horizontally across the surface on the road. The strip color is in stark contrast to the color of the road, as shown in Fig. 21, such as yellow or white against traditionally gray roads. In our deployments, we use yellow-colored duct tape stuck manually to the road. Our camera, mounted above the road and pointed downward, captures traffic driving over the yellow tape, as seen from Fig. 22, which is later processed by our algorithm, described below.

Figure 21: Contrasting rectangles to measure density

Figure 22: View of road with tape from camera

Our basic strategy for computing density is to calculate the fraction of the tape that is obscured by vehicles on every frame. To detect obfuscation of the tape, we apply two separate tests. The first test detects vehicles that have uniform coloration on their roofs, such as buses, cars, and auto rickshaws. When such a vehicle passes over the tape, it obscures the color contrast between the tape and the road. That is, without obfuscation there are neighboring pixels that have very different colors (yellow for the tape, black for the road), but with obfuscation both of these pixels are the same color (the vehicle color).

The second test detects vehicles that do not have a uniform coloration, including two-wheelers, open trucks, and the backs/sides of other vehicles. Because there is spatial variation in the vehicle’s color, this implies that there is temporal variation in color as the vehicle travels over a fixed set of pixels. Thus, we detect the presence of the vehicle by detecting changes in coloration – for a fixed set of pixels overlapping the tape – between one frame and the next. Overall, a vehicle is reported if it is detected by either of the tests above.

While this measurement reflects the density for only a one-dimensional strip of the frame, when averaged over time the result is proportional to the full two-dimensional frame density, assuming that vehicles cross the tape at their average speed for the frame.
**Intuition behind current method:** As our density estimation algorithm might seem unintuitive and complicated, we briefly mention here the issues with simple methods like background subtraction. Bengaluru buses have their tops painted in the color of road, for protection from heat and rain, as seen in Fig. 23. Subtracting a background frame (with no vehicles) from this frame (with buses), gives densities shown in Fig. 24, which misses both the buses. Similarly, comparing a frame with a contrasting color band, with a similar frame without vehicles, detects shadows as vehicles. Thus along with using contrasting color to handle buses, we need the two conditions of our algorithm, to detect all vehicles, and only vehicles without shadows.

**Our speed measurement approach:** Our speed measurement is very similar to motion vector analysis, only we use the whole frame instead of macro blocks, to match pixels between consecutive frames, for higher accuracy.

**Evaluation:** We present a subset of our evaluation results in Table. 2 and 3 where our measured densities are compared against manually observed ground truth. The density measures show about 11% error relative to manual ground-truth measurements and are robust across vehicles such as auto rickshaws, buses, cars, and two-wheelers. Our speed measurement, though computationally intensive, also gives errors of about 11% relative to manually measured speed values.
Also, our density measures are continuous, improving upon binary classifications of free-flow and congested in [10] and yielding the precise fraction of the road occupied. The density computations are done in real-time on dual-core processors unlike the heavy computations in [13], and hence are directly usable for traffic monitoring in control rooms like Mapunity [4].

Some applications: We also analyze some applications of these measurements. Using 15 hours of empirical data from Malleshwaram in Bengaluru, we calculate the morning peak hours from our density and speed measurements. An example plot of 20 mins moving average of speed and density from Jul 10 data, is shown in Fig. 25. Such empirical information can incentivize commuters to shift their travel times to non-peak hours from peak hours, an idea proposed by [2] to improve commute times.

![Figure 25: 8:15-11:15 am at Malleshwaram on Jul 10, 2012](image1)

![Figure 26: Speed vs. density](image2)

![Figure 27: Flux vs. speed](image3)

Using the same data, we also present empirical plots for the fundamental curves of transportation engineering relating density vs. speed (Fig. 26) and flux vs. speed (Fig. 27). Such empirical transportation curves can give a better understanding of traffic congestion and throughput. Though researchers have tried to characterize and model Indian traffic [14, 15, 18], efforts have either been simulation-based or limited in scale because of the manual processing overhead required, which we overcome with our automated density and speed measurement techniques.

Conclusion: Enhancing this work with implementation on embedded GPU or smartphone platforms, to reduce the video communication overhead from road to remote server for video processing, is an ongoing project. Combination of our algorithms with prior research on night vision [10] is another area that we would like to explore in future.
Publications


- Rijurekha Sen, Pankaj Siriah, Bhaskaran Raman, ”RoadSoundSense: Acoustic Sensing Based Road Congestion Monitoring in Developing Regions”, SECON’11, Salt Lake City, Utah, USA between June 27-30, 2011.


Bibliography


