Road Traffic Estimation using In-situ Acoustic Sensing

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Abstract— In this paper, we explore the efficacy of curb-side acoustic sensing to estimate road traffic conditions. We formulated a set of hypotheses which attempted to correlate traffic conditions with the ambient traffic noise. We present the evaluation of our hypotheses under various traffic conditions. Our threshold-based-classification yields 70-90% accuracy in distinguishing congested from free-flowing traffic.

Categories and Subject Descriptors: C.3 [Special-Purpose and Application-Based Systems] : Signal processing systems

General Terms: Design, Experimentation, Verification

1. INTRODUCTION

Rapid urbanization and increase in number of automobiles (two, three and four wheelers) are characteristics of developing countries like India. Coupled with adverse road conditions, driving behavior and lack of lane discipline, several cities experience severe traffic congestion. In such conditions, a traffic estimation system can be a valuable tool, both for road users and infrastructure planners. Knowledge of current and historical/typical traffic conditions can help users plan travel routes and governing bodies to better manage traffic and in planning for new infrastructure. Traffic monitoring systems used in the developed world are normally deployed on freeways and intersections, assume structured traffic and explicitly count vehicles[2][4]. These systems will most likely fail when applied to the Indian scenario, primarily due to lack of lane discipline[1][3].

The problem we address is estimation of road traffic condition in near real-time. Our quest is challenging because we want the estimation system to be minimally intrusive and low-cost. We envision a system where inexpensive, wireless-enabled, curb-side sensors are deployed widely, to collect ambient traffic-related data. A temporal-spatial collection of these signals will be analyzed and for traffic-state updates, to be sent to road users. The focus of this paper is on the sensing and signal processing aspects.

2. OUR APPROACH

The central idea of our approach is to determine traffic state as a whole rather than explicitly count or classify each vehicle. The solution aims to collect traffic-related parameters and analyze them to classify traffic as *slow-moving & congested*, or *fast* , or *static* or *empty*. The requirement of such a system is the availability of a sensing component that can give us relevant information. As a first step, we explore the efficacy of using acoustic sensors for traffic estimation.

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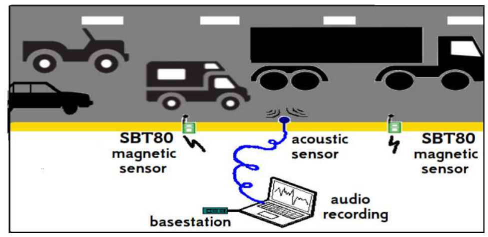

Figure 1: Curb-side sensing setup.

The intuition is as follows, different traffic states generate different kinds/levels of ambient noise/acoustic signals. The source and magnitude of noise can vary greatly depending on the kind of traffic scene, e.g., slow & congested traffic will probably have high magnitude signals originating from brakes, honks and engines. Accelerating traffic generates louder noise than freely flowing or static traffics, owing to the roaring engine. Empty-traffic will only consist of background noise from the environment. We aim to capture these differences in the acoustic signals and use them as signatures to classify traffic conditions. A plausible assumption we make is that as the density of the traffic increases, the average speed of the traffic reduces. Specifically, we aim to classify traffic into the following categories, (i) slow & congested, (ii) static, (iii) fast and (iv) empty. By slow-moving, we mean that there is frequent braking and bursty acceleration due to stop-and-go motion. The hypotheses based on which we come up with the above categorization are:

1. Accelerating or slow-moving traffic is the loudest. This is due to frequent braking, honking and engine stress due to bursty acceleration.

2. The composition of acoustic signal (power) levels over the frequency spectrum is different for different traffic states.

3. PRELIMINARY RESULTS

The objective of our measurement and analysis is to assess the capabilities and limitations of our hypotheses. Figure 1 shows our in-situ sensing setup– an omni-directional external microphone placed on the curb-side at a height of 1-2 feet connected to a laptop (for collecting logs). We deployed, collected acoustic signal logs, video-taped traffic for ground truth and analyzed these logs, at several physical locations (corresponding to different traffic scenarios and road characteristics). The setup also shows a set of magnetic sensors, which we plan to use as part of our future work.

In a deployment on a four-laned road which often experiences congestion during peak hours(Deployment #1), we

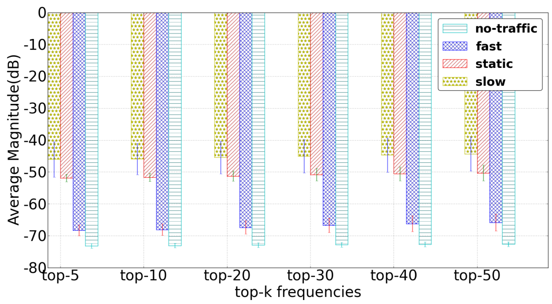

Figure 2: top-k magnitudes for classification

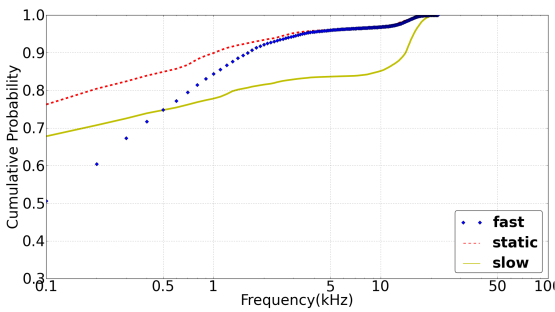

Figure 3: CDF of traffic noise levels

recorded 1 hour of ambient traffic noise and manually clipped out static, accelerating, slow-moving and fast-moving traffic segments. Each such clip was 4-5 seconds long. We wanted to study if we could correctly classify traffic states for such time segments. We convert each clip from the time domain to the frequency domain using a Fast Fourier Transform (FFT), which decomposes the signal into its frequency components. Further, we calculate average amplitude over a frequency width of 100 Hz and use it as the magnitude for that bin.

For each instance of a traffic type, we calculated the combined average amplitude of top-k frequencies (frequencies corresponding to k highest amplitudes). The intuition is to test whether the magnitude of acoustic signal (power) over top-k frequency components is distinct for different traffic patterns. Figure 2 depicts this relation. As can been seen, there is at least 20 dB difference between congested(slow-moving, static) and freely flowing(fast, empty) traffic patterns. Further, the power level in the top-5 and top-50 frequencies differs by 2 dB, and implies no additional gain from considering additional frequencies. Based on this, an initial inference is that magnitude of top-k frequencies is indicative of traffic pattern. In this case, a threshold which lies between the 20 dB difference can separate congested traffic from non-congested. To test our findings, we chose unseen data from the same deployment. With a -60 dB threshold to seperate fast from slow-moving traffic, we achieved 92% accuracy.

Next, we analyzed the contribution of all the frequency components of the signal. Based on the magnitudes associated with each frequency, we plotted a CDF of the entire frequency spectrum. The intuition is as follows, slow-moving/heavy traffic predominantly generates high frequency noise, while static-traffic has contributions from the lower frequency spectrum owing to idle engine noise. A CDF can be used to analyze whether this is indeed the case.

Figure 3 shows the CDF of traffic noise on a near straight-road deployment (Deployment #2) outside the college campus. The road is two-laned on each side and often experiences high-density congested traffic during peak hours. Note that the x-axis is in log scale. As seen from the figure, frequencies below 5000 Hz contribute 95% of the total magnitude for both fast and static traffic, and 80% for slow-moving traffic. With slow traffic, 95% of total amplitude is contributed by frequencies below 15 KHz. Slow traffic at this location is a result of frequent braking and bursty acceleration due to stop-and-go motion. Fast and static traffics, do not suffer from these effects and appear similar in the frequency-amplitude profile. This difference in contributions can classify slow-moving traffic from fast and static traffics. Note that this inference is different from the one we hinted at using Deployment #1 (using average amplitude of top-k frequencies). In that case, we were able to distinguish congested(slow-moving and static traffic) from free-flowing(fast and empty) conditions. Further, here, the average magnitude of slow-moving traffic was only 10 dB higher than that of empty-traffic, making it difficult to use the top-k approach for traffic classification. Upon testing the 95%-5kHz threshold for CDF, we achieved 74% accuracy in classifying fast and slow traffics.

We repeated the above data collection and analysis process at different locations experiencing both congested and free-flowing traffic at different times of the day. In several cases, the CDF approach did not yield distinguishable features while the approach of using the average magnitude of the top-k frequencies for classification seemed promising. For example, the CDF of traffic in Deployment #1 has consistent contribution by the entire frequency spectrum for all kinds of traffic.

4. CONCLUSIONS AND FUTURE WORK

As part of this work, we assessed the efficacy of using curb-side acoustic sensing for traffic estimation. We formulated a set of hypotheses which attempted to correlate traffic conditions with the ambient traffic noise. We presented the evaluation of our hypotheses under various traffic conditions. Through our analysis we determined that ambient acoustic sensing is selectively applicable for traffic estimation.

As part of future work, we can incorporate sophisticated learning and classification algorithms applied to acoustic signals[5] for traffic classification. Also, we intend to incorporate multi-modal sensing into our approach in the future. Previous studies were able to show correlation between traffic state/density and magnetic sensors readings, hinted at classifying moving and static traffic reliably. Currently, we are analyzing multi-modal acoustic and magnetic sensor data towards distinguishing traffic state under all conditions.

5. REFERENCES

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