Detecting Traffic Congestions Using Cell Phone Accelerometers

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Abstract
In this paper, we propose a system that detects traffic congestions by using cell phone accelerometers, which have many advantages (e.g. energy-efficient, unobtrusive, impervious to environmental noise, etc.). However, it is challenging to extract well-targeted and accurate features (e.g. speed) for detecting traffic congestions in a complex daily-living environment using a single cell phone accelerometer. The proposed system comprises a vehicular movement detection module, and a module for likelihood estimation of traffic congestions. Experimental results based on real datasets have demonstrated the effectiveness of the proposed system.

Author Keywords
Traffic Congestion; Accelerometer; Cell Phone

ACM Classification Keywords
H.4.0 Information Systems Applications: General

Introduction
Traffic congestion detection is becoming increasingly important with the increasing number of urban vehicles. Traditional traffic congestion detection solutions (e.g. road-side sensors, floating vehicles, etc.) suffer from high installation and maintenance costs, limited coverage and poor timeliness [1]. This poster proposes an alternative solution using ubiquitous cell phones.

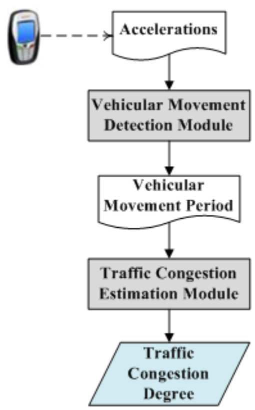

Figure 1. The pipeline of the proposed traffic congestion detection system.

The pioneering works of using cell phones for traffic congestion detection either work in a dedicated manner (i.e. the cell phone probes are deployed on specific roads, and the sensed data are dedicatedly collected to estimate traffic congestions of these roads) [1, 2], or rely on power-hungry sensors (e.g. GPS) [3]. However, since cell phones could be carried to almost everywhere in complex daily-living environment, the cell phone based traffic congestion detection system should be *adaptive* (i.e. it has to determine whether the cell phone users are on vehicles), *unobtrusive* (i.e. it has to work automatically without user intervention) and *energy-efficient* (i.e. it has to be independent on the power-hungry sensors of cell phones, such as GPS).

To this end, we propose a traffic congestion detection system using cell phone accelerometers. To the best of our knowledge, this is the first work that uses only cell phone accelerometers for detecting traffic congestions. The pipeline of the proposed system is shown in Figure 1. Once a traffic congestion event is detected, the cell phone could pinpoint its location (e.g. by temporarily turning on GPS) and report it to a central traffic management system.

System

Vehicular Movement Detection Module

Traffic congestion detection is reasonable only when the cell phone users are traversing by vehicles. The vehicular movement detection module takes the 20Hz accelerations as input. It firstly uses a motion classifier to continuously classify the current transportation mode into one of the three motions: *stationary*, *pedestrian* and *vehicular*. Then, it heuristically detects the vehicular movement periods based on the continuous motion classification results.

Since the orientation and placement of cell phones could not be controlled in daily lives, we compute the L2-norm of the 3-axis accelerometer readings as basic input data. Then, the motion classifier is built by two steps: First, we use a sliding window (with window size W_{MC} and step size S_{MC}) as the period of classification, and various features that have been proven to have strong discriminative ability for motion classification are extracted from the sliding window, including time-domain features: mean, variance, minimum, maximum and range and frequency-domain features: energy, entropy, peak frequency power and the magnitudes of the DFT (Discrete Fourier Transform) coefficients between 1-3Hz. Second, a simple C4.5 decision tree classifier is created for motion classification based on the training data, considering the computation capability limitation of cell phones.

The continuous motion classification could generate a sequence of motions. We heuristically determine the vehicular movement periods based on a duration threshold T_{VM}: a vehicular movement period is initialized if more than T_{VM} seconds of vehicular motion is detected, and over if more than T_{VM} seconds of pedestrian motion is detected. This is based on the intuition that it always requires an intermittent pedestrian movement period between consecutive vehicular movement periods [4]. A vehicular movement period is then represented as a sequence of motions (we call it *TMS* (temporal motion sequence)). Besides vehicular motions, a *TMS* might include short-term stationary motions (e.g. stopping due to traffic congestion or traffic light) and pedestrian motions (e.g. walking on a bus).

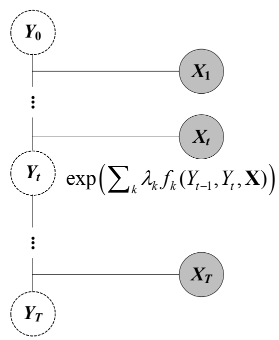

Figure 2. Traffic congestion estimation by a linear-chain CRF.

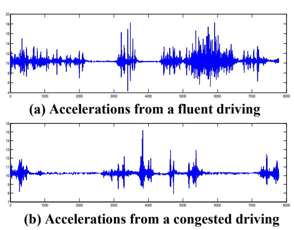

Figure 3. The difference of data characteristics from fluent and congested driving periods.

Traffic Congestion Estimation Module

After detecting a vehicular movement period, we estimate its traffic congestion degree based on a conditional random field (CRF). CRF is a discriminative model that outperforms generative models (e.g. hidden Markov model) in sequence labeling problem [5]. Thus, it is suitable for our traffic congestion estimation problem, which aims to estimate the temporal transformation of traffic congestion degree during a specific vehicular movement period.

We use a linear-chain CRF (as shown in Figure 2) for our traffic congestion estimation problem. The CRF consists of two kinds of nodes: nodes **Y** which represent the sequence of states to be inferred given the sequence of observations denoted by nodes **X**. Since traffic congestion is not an instant state, we use a sliding window (with window size W_{TC} and step size S_{TC}) as the period of estimation. Thus, observation X_t and state Y_t denote the calculated features and the corresponding traffic congestion degree of the sliding window at the t^{th} time slot. The CRF defines the conditional probability of a state sequence $\mathbf{Y} = Y_1Y_2 \ldots Y_T$ given an observation sequence $\mathbf{X} = X_1X_2 \ldots X_T$ as Equation 1, where f_k is a feature function (Y_0 is an empty state for simplicity of defining the model) and λ_k is the weight of f_k, $Z(\mathbf{X})$ is a normalized factor.

$$P(\mathbf{Y} \mid \mathbf{X}) = \frac{1}{Z(\mathbf{X})} \prod_{t=1}^{T} \exp\left(\sum_k \lambda_k f_k(Y_{t-1}, Y_t, \mathbf{X})\right) \qquad (1)$$

In order to define the feature functions $\mathbf{F} = \{f_k\}$, we introduce the following features extracted from the sliding window over the *TMS* obtained from the specific vehicular movement period. Figure 3 shows the difference of data characteristics from fluent and congested driving periods, which inspires the selection of the following features.

- **Stationary Period Ratio** (SPR): Traffic congestion usually gives rise to longer stationary time. SPR is the ratio of the total time duration of stationary motions within the sliding window to the time duration of the sliding window itself.
- **Motion Switch Frequency** (MSF): Traffic congestion is often characterized as a repeated "stop-and-go" flow. MSF is the frequency of switches between stationary motion and vehicular motion within the sliding window.
- **State Switch Smoothness** (SSS): It is very unlikely that the traffic congestion degree encountered by a user switches frequently in a short interval during a *TMS*. SSS tests whether there are two consecutive identical states in the three consecutive estimated states. For example, the feature is true for "AAB" or "ABB" and false for "ABA" or "ABC".

Given N sequences of training data $\{(\mathbf{X}^{(n)}, \mathbf{Y}^{(n)})\}$ (n=1…N), learning the parameters $\mathbf{\Lambda} = \{\lambda_k\}$ is done by maximizing the conditional log-likelihood as Equation 2. Once the parameters $\mathbf{\Lambda}$ have been learned, the model can be used to infer the traffic congestion degree Y_T as Equation 3 given a *TMS* **X**.

$$L(\Lambda) = \sum_{n=1}^{N} \log P(\mathbf{Y}^{(n)} \mid \mathbf{X}^{(n)}) \qquad (2)$$

$$Y_T = \arg\max_{Y_t} P(Y_t \mid \mathbf{X}, \Lambda) \qquad (3)$$

Experiment

We evaluated our system based on real dataset collected by using the volunteers' cell phones. The

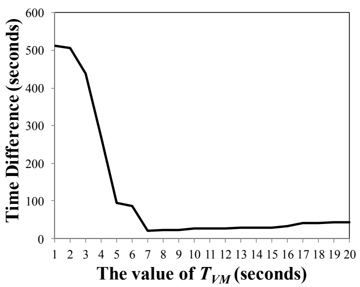

Figure 4. The performance of vehicular movement period detection.

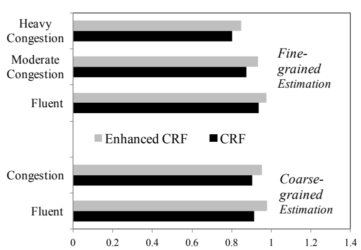

Figure 5. The performance of traffic congestion estimation.

dataset contains 19 hours of accelerometer traces. Three kinds of ground-truth labels are provided by the volunteers for each vehicular movement period. The first is the starting and ending time. The second is the traffic congestion degree: fluency, moderate congestion or heavy congestion. The third is the fine-grained vehicular motion type: by car or by bus.

First, we evaluate the ability of detecting vehicular movement periods. Each test case contains the true starting and ending time (t_{ts} and t_{te}) of the involved vehicular movement period, and we could obtain the detected starting and ending time (t_{ds} and t_{de}) based on the vehicular movement detection module. We test the *time difference* (the average value of $|t_{ds} - t_{ts}|$ and $|t_{de} - t_{te}|$) by adjusting T_{VM} (W_{MC} = 3.2 seconds, S_{MC} = 1 second). The result is shown in Figure 4. A longer T_{VM} helps to detect the vehicular movement periods more accurately, but also increases the detection latency. The optimal performance is roughly achieved when T_{VM} = 7 seconds (the *time difference* is about 15 seconds).

Second, we evaluate the performance of estimating traffic congestion degree based on 10-fold cross validation. We set W_{TC} = 10 minutes, and S_{TC} = 2 minutes. The coarse-grained estimation is to classify the traffic congestion degree into fluency and congestion, and the fine-grained estimation is to classify into fluency, moderate congestion and heavy congestion. Figure 5 shows the accuracy of our traffic congestion estimation method (i.e. CRF), which could well estimate fluency and congestion, but weaker in distinguishing between moderate congestion and heavy congestion. This might be because that the boundary of the two degrees is not that clear for precise labeling. Besides, we also evaluate the effect of fine-grained vehicular motion type (by car or by bus) on traffic congestion estimation. We add the fine-grained vehicular motion type as an extra feature, and test the Enhanced CRF. The accuracy of Enhanced CRF is obviously higher than that of CRF. The reason is that different fine-grained vehicular motion types could have totally different driving patterns, resulting in different data characteristics of traffic congestion.

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