Automatic Incident Detection in Freeways by using Bluetooth Based Tracking

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Introduction

Automatic incident detection (AID) methods are an important component of intelligent transportation systems (ITS). Traffic incidents are the cause of most of disruptions in freeway traffic flow, therefore accurate detection of incidents is of vital importance to take actions aimed at restoring a normal traffic flow. The majority of current AID methods rely on data provided by magnetic loop detectors [4, 6]. These detectors are considered as the traditional sensors for monitoring the traffic flow, i.e. velocity and occupancy, at freeways. However, magnetic loop detectors have many disadvantages: their installation is complicated and expensive, and their failure rates are quite high. These drawbacks call for investigating new sensor technologies and developing new AID methods for their data.

Bluetooth (BT) is an emerging technology in traffic estimation that allows to track vehicles equipped with BT devices [2]. The AID method proposed in this work relies on data provided by BT sensors placed along a freeway. BT readers capture an unique electronic identifier, denoted as Machine Access Control (MAC) address, and the time stamp of all passing vehicles containing a BL device. A monitoring system, that receives the data from all the BT readers, calculates travel times by matching these identifiers at successive sensors. The data is processed to eliminate multiple detections on the same vehicle (e.g. several devices in a bus) and outliers.

The objective of the current work is to develop an AID method relying exclusively on data provided by BT sensors. After presenting the method, it will be evaluated using real data measured by a network of BT sensors placed along Ayalon Highway, which is a major intracity freeway in Tel Aviv, Israel. The estimations obtained with the proposed method will be compared to the incident report facilitated by the Ayalon Highway company.

Model-based anomaly detection

We present a model-based anomaly detection framework designed for analyzing streaming data from network of BT sensors along a freeway. The output of this method is an estimation of the occurrence of an incident in a given freeway section between two consecutive BT sensors. The method (see Figure 1) is composed of two phases: a prediction and an anomaly detection. Roughly speaking, the predictor estimates the travel time 5 min ahead using information measured by the network of BT sensors, and the anomaly detector triggers an alarm if the mismatch between the prediction and the measured travel time is higher than a threshold. These two phases are briefly described in the sections ahead.

a) Predictor

The first stage of the proposed AID method is based on performing a prediction of the travel time 5 min ahead. The predictor uses as input data information collected by the network of BT sensors in the previous 15 min. We use a machine learning technique called gradient boosting trees (GBT) for regression as algorithm to built the predictor of the travel time. This method has been successfully applied in many fields, including travel time prediction but using different type of data [7] . This technique builds a predictor in the form of an ensemble of decision trees, where the trees are trained sequentially and each

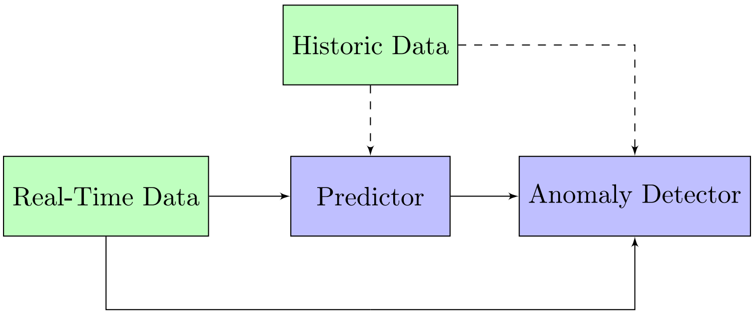

Figure 1: Model-based anomaly detection framework. Dashed lines represent off-line processes and solid lines represent on-line processes.

new tree is fit to the residual of the predictor at the previous stage. The reader is referred to [3] for a more detailed exposition. We note that it is important to use a loss function, which makes the model learned during the training robust to anomalies [1]. In this case we use least absolute deviation instead of the usual least squares. Other details about the training of the predictor are omitted for the sake of brevity.

Figure 2 shows the travel time prediction performed by the GBT model during a particular day at two consecutive freeway sections (sections between the sensors BTAY17, BTAY18 and BTAY19). The performance of the prediction can be quantified by mean of different indexes. We use here the mean absolute percentage error (MAPE) for which the obtained predictor reaches values less than 4%.

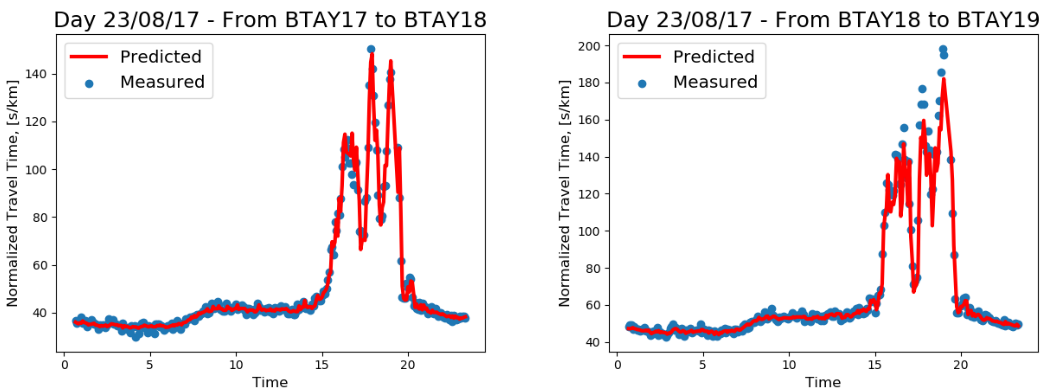

Figure 2: Examples of travel time predictions obtained by the GBT predictor. Travel time has been normalized with respect to the length of the segment.

b) Anomaly Detector

The second stage of the AID systems consists on an anomaly detector that compares the prediction to the measured travel time. This mismatch is compared to a threshold related to the variability of the regression residuals along the time of the day. The variability of the regression residuals are obtained by applying the median absolute deviation (MAD) within a moving window to the relative residuals of the training set versus the time of the day. After that, a Savitzky–Golay filter [5] is applied in order to smooth the estimation. Finally, the obtained signal is scaled to obtain thresholds for warnings and alarms. These two scaling factor are tuning parameters of the AID method. The process explained in this section is illustrated in Figure 3. Observe that the time-dependent nature of these threshold accounts for the fact that at some hours the prediction is more challenging (e.g. during rush hours).

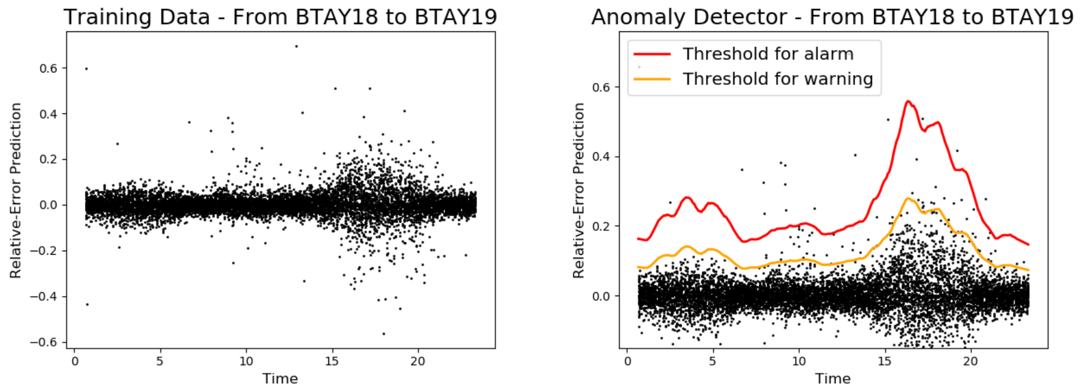

Figure 3: Relative residuals (left) and thresholds of anomaly detector (right).

Preliminary results using real data from Ayalon Highway

This section presents preliminary results of the proposed AID method using real data from Ayalon Highway. The same data has been used to illustrate the predictor and anomaly detector that compose the model-based anomaly detection method presented in the previous section.

The method proposed has been applied to days for which report with recorded accidents is available. Recorded accidents during the days that the method is applied are given below:

- Day 22/08/17. Several accidents were reported from BTAY18 to BTAY19:
  - Car accident with casualties, 10:32 to 12:15.
  - Car accident with casualties, 18:30 to 20:27.
  - Car accident with no casualties, 20:46 to 22:54.
- Day 23/08/17. No accidents were reported from BTAY18 to BTAY19.

The estimations obtained using the proposed methods are shown in Figure 4. It is appreciated a good correspondence between the estimated accident and the accident recorded in the report. It is also remarkable that in a day without accidents, there are not false alarms. The proposed method is promising, but it should be further evaluated over longer periods of time in order to validate these preliminary conclusions.

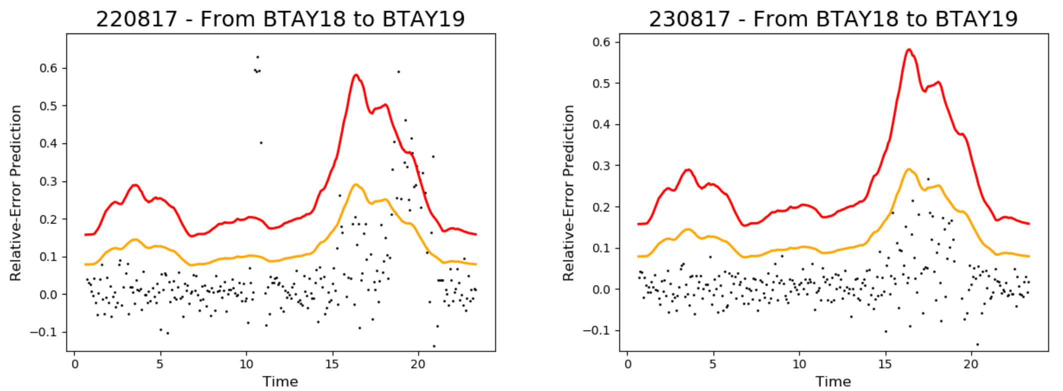

Figure 4: Estimation of incidents using proposed method. An incident is detected when the relative-error prediction is above the threshold for alarm (red line).

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