Vehicle detection and speed estimation with PIR sensors

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ABSTRACT

Reliable and accurate traffic sensing systems are the basis of the effectiveness of *Intelligent Transportation Systems*, which mitigate traffic mobility and safety issues. To promote vast adoption of ITS technologies, rapid deployment and auto calibration of traffic sensing systems are critical. Aiming at the development of an advance traffic sensing system for construction zones, this poster presents our preliminary results for detecting vehicles and estimating traffic speed, by applying signal processing and machine learning techniques using the *Passive Infrared* (PIR) sensor data.

1. MOTIVATION

Construction activities on sections of roads (known as work zones) commonly introduce mobility and safety issues, such as the development of queues and hence rear-end crashes. ITS is expected to mitigate such issues, by measuring the real-time traffic conditions, and taking actions accordingly. The performance of ITS relies on the quality and quantity of traffic data (e.g., traffic flow, speed). Particularly, the work zones by nature is dynamic: the scale (miles) and duration (days to years) of construction projects vary across work zones. To promote the adoption of ITS in work zones, the ITS devices should be mobile, robust, and self-contained, without requiring much installation effort or external power lines.

With the above vision, we are developing an advanced traffic sensing systems specifically for work zones. This poster presents our preliminary test results in measuring traffic volume and speed, using PIR sensors.

2. RESEARCH OBJECTIVE

Rapid deployment requires the sensor to be energy efficient and non-intrusive (placed on the side of roads without interfering the traffic). PIR sensor is low-cost and low-power. Correspondingly, the collected PIR data (temperature in view) is relatively less informative. Hence, advanced algorithms are necessary for extracting desired traffic information (traffic volume and speed) from PIR data. In this preliminary test, we apply signal processing and machine learning techniques to detect vehicles and estimate the traffic speed.

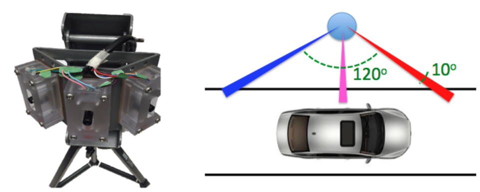

Figure 1: PIR sensor array: Left: Three PIR sensors are integrated in one device. Right: The PIR sensor array is designed to be placed by the road side.

We used an array of three identical PIR sensors (Melexis MLX90614) connected to a main board through SMBus as shown in Figure 1. Each sensor has a field of view of 10 degrees, and spans a 120 degrees detection zone. The PIR sensor array is deployed by the side of the road for measuring traffic volume and speed.

The power consumption of each PIR sensor is around 15mW in continuous operation, and it measures the average temperature in its field of view with a rate of 12Hz and a resolution of 0.1°C.

3. METHODS

3.1 Vehicle detection

The recorded data is divided into windows of size w, and classified as *vehicle* or *non-vehicle* using supervised classification. Generally, the temperature of a vehicle is different from the ambient temperature. Therefore, when a vehicle passes in front of the sensor, an abrupt change in the temperature is recorded. This subsection presents a method to detect windows of time that contain such an abrupt temperature change.

A high-pass filter is used to remove the effect of gradual ambient temperature changes due to weather conditions. The window size w is varied from $0.25\,s$ to $6.25\,s$ with a $\frac{1}{5}w$ offset. The signal data in each window is averaged using a Hamming function, which allows for higher weights for measurements in the center of the window. Thus, the data used

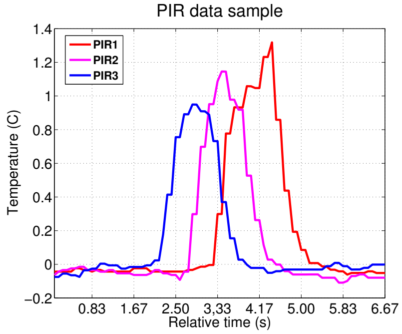

Figure 2: Time shifts: The time shifts in the signals from three PIR sensors.

for classification is reduced to three dimensions – one for each PIR sensor. These vectors are used to train logistic regression and *Gaussian mixture model* (GMM) classifiers.

3.2 Speed estimation

Since the sensor array has three PIR sensors in different orientations (Figure 1), the temperature changes associated with a passing vehicle are recorded at different times by each sensor (Figure 2). Convolution is applied to the three signals to obtain the shifts of the signal spikes.

Three time shifts are obtained $\Delta t_{32}, \Delta t_{21}, \Delta t_{31}$, where Δt_{ij} represents the time shift of spikes from PIR i to PIR j. Two linear regression models are compared:

$$v = c_1 + c_2 \Delta t_{32} + c_3 \Delta t_{21} + c_4 \Delta t_{31}, \qquad (t\text{-}model),$$
$$v = c_1 + c_2 / \Delta t_{32} + c_3 / \Delta t_{21} + c_4 / \Delta t_{31}, \qquad (1/t\text{-}model).$$

The first *t-model* simply takes the time shifts as features in linear regression. Alternatively, since speed is inversly related to travel time, the *1/t-model* uses the inverse of time shifts as features.

4. RESULTS

4.1 Vehicle detection accuracy

In order to assess the accuracy of vehicle detection, nine-fold cross-validation is used. The detection accuracy is measured both in terms of false positives and false negatives across all folds. Here, a false positive is a detection that does not correspond to a true vehicle, and a false negative is a vehicle that was not detected. The ground truth is obtained from GPS sensors in the vehicles. Figure 3 compares the error rates between the various types of models. Overall, the logistic regression model achieved the best performance, with zero false positives and only one false negative out of 288 vehicles. It is also worth noting that this peak performance occurs at a window size of 1.25 seconds. This is an acceptable latency for most applications, and a lower latency can be achieved at some cost of accuracy.

4.2 Speed estimation accuracy

After vehicles are detected, a similar cross-validation scheme is used to evaluate the performance of the speed estimation. Several models are tested, which vary the regression terms and methods for computing the time shifts. Figure 4 shows

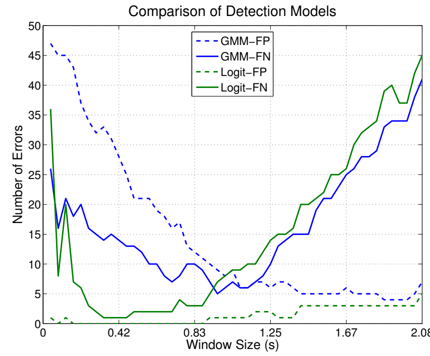

Figure 3: Detection performance of several models: The performance of vehicle detection depends on the models used and the window size. Overall, the logistic regression model provides the best result.

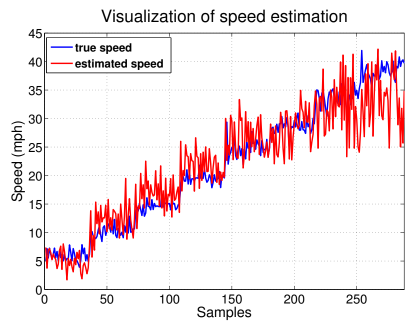

Figure 4: Speed estimation using linear regression: Blue: true speeds from GPS data; Red: estimated speeds from PIR data.

a comparison of the true and estimated velocities over all of the data. The best model, which uses the center-of-mass method to compute the time shift and regresses the speed onto $1/t$ achieved an RMS error rate of about 4 *mph* per trip. Again, the ground truth comparison is obtained from GPS sensors in the vehicles. This is a fairly accurate measurement for most traffic monitoring applications.

5. CONCLUSION AND FUTURE WORK

This poster shows promise for the use of PIR sensors as an inexpensive, low energy sensing technology for traffic estimation. In particular, when equipped with the appropriate data processing techniques, the sensor is able to detect passing vehicles with a high degree of accuracy.

Furthermore, it is able to estimate the speed of passing vehicles with reasonable accuracy. One main factor for the speed estimation error is the varying distance of vehicles from the sensor. Currently, we are conducting more complex statistical analysis, integrating a more advanced 16×4 PIR sensor array, as well as developing semi-supervised approaches for achieving better performance in vehicle detection and speed estimation.

Vehicle Detection and Speed Estimation from PIR Data

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Background and Motivation

Intelligent Transportation Systems (ITS) are expected to resolve the increasingly critical issues such as estimating traffic congestion and detecting incidents.

The success of ITS relies on the quality and quantity of traffic data (e.g., flow, speed). Critical requirements for traffic sensor networks are:

- Low-cost, so sensors can be densely deployed.
- Low-power, to minimize maintenance and weight (deployment effort).

*Passive infrared (*PIR) sensing is a low-cost and low-power technology to measure temperature, which in principle be linked to traffic quantities. However, data processing algorithms are needed to extract accurate and meaningful traffic information from the sensors.

Objective: Use combination of signal processing and machine learning techniques to detect vehicles and estimate their velocities from PIR sensor data.

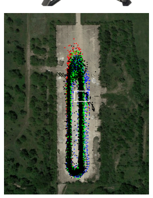
Data Collection

Goal

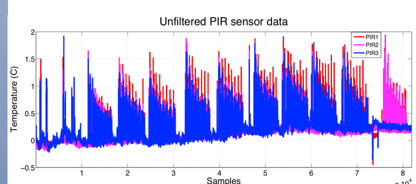
Collect passive infrared data, as well as GPS data for ground truth timestamps and velocities

Process

- 4 vehicles drive in a circle at varying speeds
- A small sensor zone is marked around the PIR sensor
- Each vehicle is equipped with a GPS smartphone to provide accurate speed estimates.
- Trajectories are parsed to obtain ground truth velocities each time the car drives through the sensor zone



GPS trajectories from field test in Rantoul, IL.



Raw PIR data collected from 10:13 to 12:06 on Nov-11-2014. Ambient temperature is slowly increasing.

Vehicle Detection

Goal

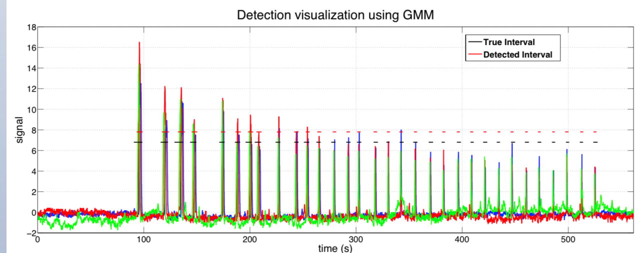
- Use spikes in temperature to detect vehicles.
- How to determine detection threshold?
- How to utilize information from all three sensors?

Preprocessing

- High pass filter - remove changes in ambient temperature.
- Discretize time into overlapping windows.
- Use Hamming window to compute average temperature during each window.
- Repeat for all three sensors.

Algorithm

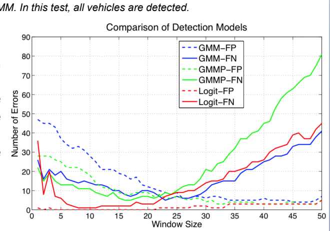
- Classify windows as "vehicle" or "no vehicle".
- Use GMM and logistic regression - compare results using cross validation.



Vehicle detection result using GMM. In this test, all vehicles are detected.

Result

- The best model is logistic regression with a window size of 10.
- In this model, no false positives were reported and only one false negative occurred out of 288 vehicles.
- The PIR sensor can reliably measure the vehicle flow (veh/hr) on a roadway.



Comparison of performance of different detection models. FP: False positive; FN: False negative.

Conclusion

- Results demonstrate that the PIR sensor is reliable for vehicle detection and speed estimation.
- The low cost and low energy usage make PIR very competitive sensor for practical applications.

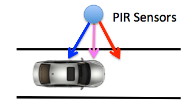
Future Work

- Further improvements to velocity estimation, more advanced preprocessing, and auto calibration.
- Robustness to ambient temperature, distance to the vehicle, and sensor orientation need to be further investigated.

Speed Estimation

Goal

- Estimate velocities of vehicles using time shifts between the three spikes.
- How to measure time shifts?
- How to best use information from all three sensors?

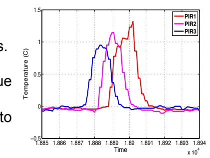


Preprocessing

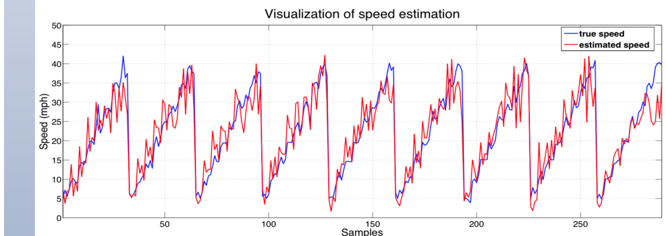
- High pass filter - remove changes in ambient temperature.
- Use pre-labeled vehicle instances with known velocities.

Algorithm

- Use convolution to measure shifts between pairs of sensors.
- Shifts can be estimated using *max* or *center of mass.*
- Use linear regression to correlate the time shift with the true velocity.
- Use 1/t for all the sensors - travel time is inversely related to velocity.
- Compare various models using cross validation.



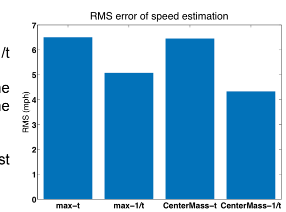
Visualization of time shifts.



Speed estimation result using linear regression.

Result

- The best model is linear regression, using 1/t and center of mass for all three time delays.
- There is also improvement from using the center of mass of the convolution instead of the max.
- Obtained a RMS error of roughly 4 mph.
- This is a fairly accurate measurement for most applications.



Comparison of speed estimation models.

Acknowledgments

- The PIR sensor is provided by Prof. Christian Claudel, KAUST.
- Setup of the hardware is assisted by Dr. Jiming Jiang, KAUST.
- Access to the field test location at the *Advanced Transportation Research and Engineering Laboratory* (ATREL) was provided by the *Illinois Center for Transportation*.
- The field test was assisted by Immanuel Stern and Fangyu Wu.