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Multi-Sensor Traffic Data Fusion

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MULTI-SENSOR TRAFFIC DATA FUSION

FINAL REPORT (PATH MOU-3021)

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Multi-Sensor Traffic Data Fusion

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ABSTRACT

This report describes unique surveillance system on a section of I-80 freeway in the city of Emeryville. The system, called the Berkeley Highway Laboratory (BHL), consists of eight dual loop detector stations along the freeway section, and 12 video cameras. Advanced machine vision algorithms were developed to process the video data to generate vehicle trajectories. Efforts are underway to fuse the loop and video detector data to obtain detailed and accurate information on traffic operating conditions

Keywords:
Freeways, detectors, Machine Vision, Traffic Flow

EXECUTIVE SUMMARY

The deployment of Advanced Traffic Management and Information Systems (ATMIS) requires thorough evaluation through simulation prior to field implementation. Several simulation models are available to provide both offline evaluation of ATMIS strategies, and online operation of proposed systems. However, the application of simulation models requires accurate and detailed data to calibrate the model parameters and validate the model outputs against real-world conditions.

Loop detectors provide macroscopic parameters (flow, density, speed), but they do not provide vehicle trajectories that are essential for detailed modeling of vehicle interactions. A large number of real world vehicle trajectories can only be obtained from processing video data. This in turn requires a video surveillance system with sufficient area of coverage and technologies to automatically and robustly obtain trajectories from the video data.

We have developed a unique surveillance system on a section of I-80 in the city of Emeryville. The system, thereafter called the Berkeley Highway Laboratory (BHL), consists of eight dual loop speed trap detector stations along the freeway section, and 12 video cameras on top of the 30 story building adjacent to the freeway section. The coverage of the cameras overlaps with the location of 8 loop detectors.

The BHL is fully operational. We have already collected video tapes of over 12,000 camera-hours. We developed and tested advanced machine vision algorithms to generate vehicle trajectories. The results to date from the processing of data indicate that the generated trajectories by the machine vision algorithm are very accurate. We have explored ways to use the data from both the video and the loop detectors in a synergistic manner to exploit the strengths of each surveillance system.

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1. INTRODUCTION

The deployment of Advanced Traffic Management and Information Systems (ATMIS) requires thorough evaluation through simulation prior to field implementation. Several simulation models are available to provide both offline evaluation of ATMIS strategies, and online operation of proposed systems. However, the application of simulation models requires accurate and detailed data on traffic operating conditions to calibrate the model parameters and validate the model outputs against real-world conditions.

Conventionally, traffic flow parameters and traffic performance data have been generated from loop detectors or a small number of instrumented vehicles. Loop detectors show robust detection performance, but provide macroscopic parameters (flow, density, speed). They do not give vehicle trajectories that are essential for detailed modeling of vehicle interactions. Instrumented vehicles generate long trajectories with detailed maneuvering parameters, but we only get a single trajectory for a single driver. On the contrary, a large number of real world vehicle trajectories can be obtained from processing video data. However, the technologies to automatically and robustly obtain trajectories from video data are very challenging. Thus, automatically generating vehicle trajectories from video data has still been in an experimental level.

This report describes our efforts to building a video database, and generating usable vehicle trajectories from it based on advanced machine vision algorithms. We have also investigated ways to use data from the loop detectors to improve the performance of the video-based tracking system.

2. DATA COLLECTION

We have developed a unique surveillance system on a section of I-80 in the city of Emeryville. The system, thereafter called the Berkeley Highway Laboratory (BHL), consists of eight dual loop speed trap detector stations along the freeway section, and 12 video cameras on top of the 30 story Pacific Park Plaza apartment building. The system consists of:

Video Surveillance System: Twelve fixed mount video cameras configured to provide continuous coverage of the freeway, with one camera's surveillance region overlapping the next one. In addition, there are two pan-tilt-zoom (PTZ) cameras connected to Caltrans District 4 and UC Berkeley. The twelve fixed mount cameras are connected to studio-grade video tape recorders (VTRs), housed on top of the Pacific Park Plaza. The installation of the system is shown in Figure 1.

Data are recorded each weekday during the commute periods. Tapes are collected and replaced daily and then delivered to the PATH Headquarters at the Richmond Field Station on a weekly basis, where they are catalogued and used for off-line data processing and analysis.

Loop Detectors: There are eight loop detector stations at approximately 1/3 mile apart.

The standard Caltrans detector station uses a Model 170 controller sampling the loop sensors at 60 Hz and provides 30 second aggregate values of vehicle count (flow), occupancy and speed. The system currently utilizes the I-880 Caltrans software that preserves the 60 Hz event data. The data are temporarily stored in a laptop computer inside the controller cabinet and continually transmitted to UC campus via a wireless modem where they stored and processed.

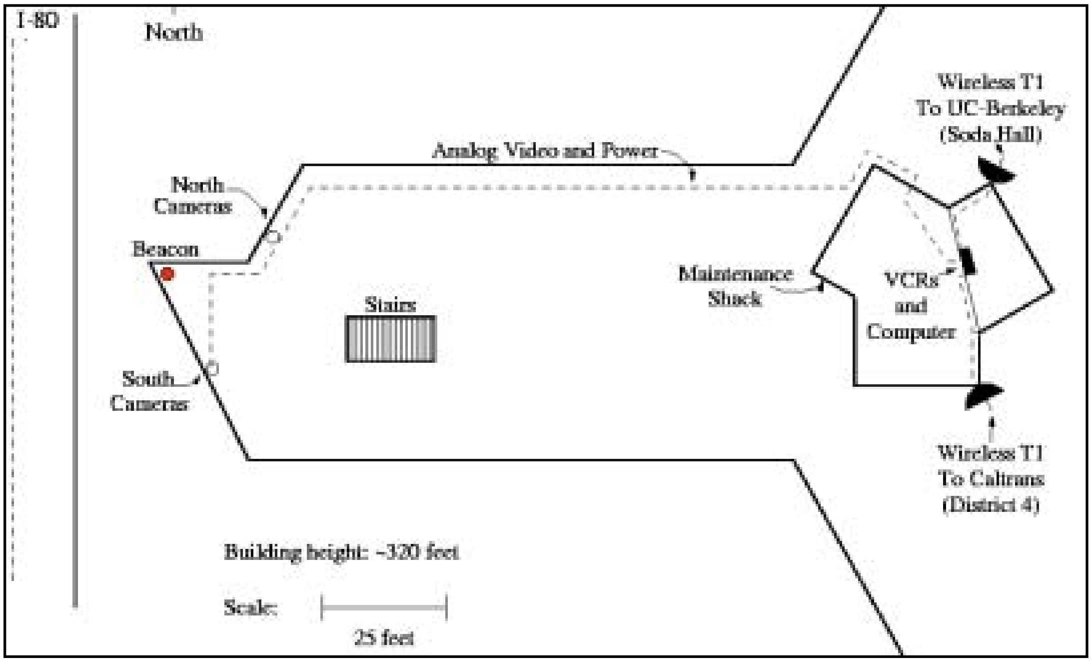

Figure 1. The BHL Video Surveillance S—Roof of the Pacific Park Plaza Building

The coverage of the video surveillance system overlaps with the locations of the loop detectors. The configurations of the cameras and the loop detectors for I-80 north- and south- bound are shown in Figures 2 and 3.

We have collected video tapes of over 12,000 camera-hours. For some of the video data, the loop detector data is also available (at the time it was collected). We have digitized some of the video data for the automated trajectory generation.

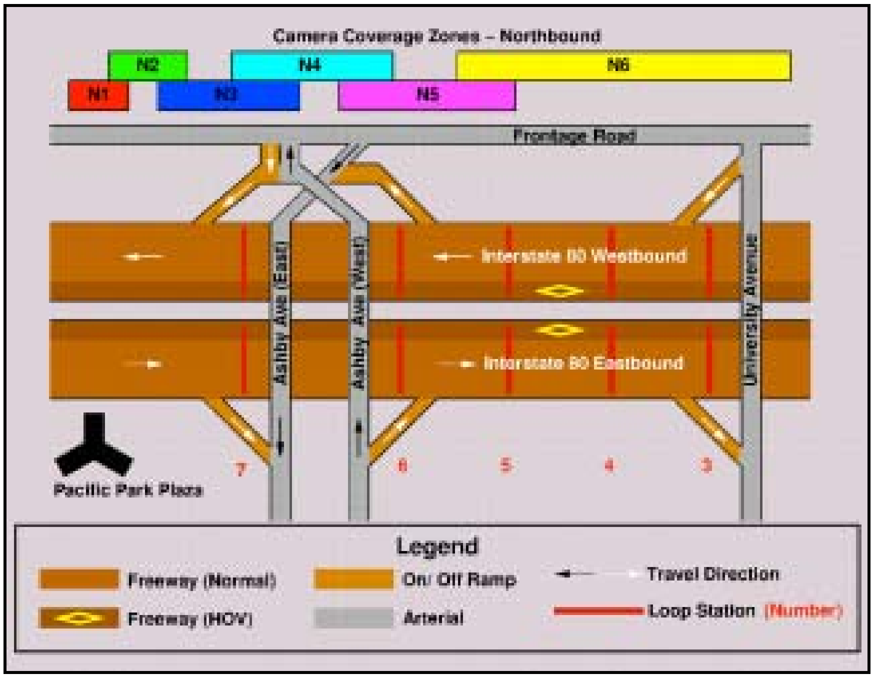

Figure 2. Video Camera Coverage Zones, and the Locations of the Loop Detector Stations I-80 northbound

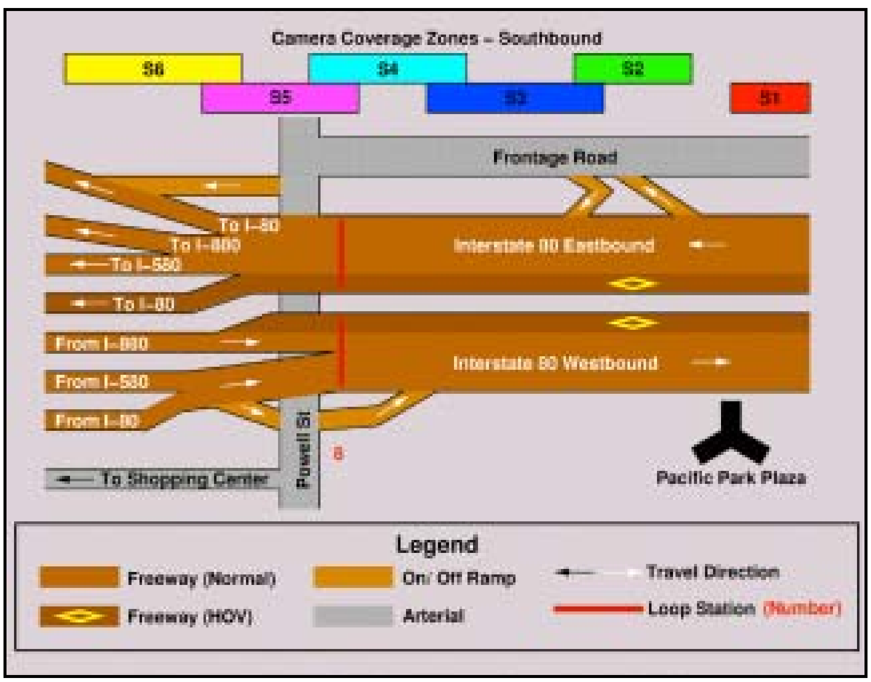

Figure 3. Video Camera Coverage Zones, and the Locations of the Detector Loop Stations I-80 Southbound

3. VEHICLE IDENTIFICATION

3.1 Loop-Based Algorithm

There are two distinct efforts toward improving loop-based vehicle re-identification. The first uses on/off detectors and attempts to re-identify by looking at vehicle platoons; the second matches loop signatures using neural networks and Fourier analysis. Loop signatures have also been used to classify vehicles, obtaining results that are remarkably similar to the video-based classifier. The process and results are described in detail elsewhere [4], [5].

3.2 Video-Based Algorithm

We extract vehicle trajectories from the raw video streams. The computer vision algorithm for generating the vehicle trajectories needs to be accurate and reliable. We face several challenges in producing reliable vehicle trajectories:

- The tracking targets (vehicles) vary in sizes, shapes, and colors.
- Our video data includes various times and weather conditions. Thus, the illumination conditions, such as the brightness of image and the direction of the shadows, vary.
- We need to deal with the occlusions among vehicles due to the presence of overpasses.
- Traffic conditions vary, and many of the tracking algorithms degrade with heavy traffic congestion, where vehicle moves slowly, and the distances between vehicles are small. In this case, motion-based vehicle detection and background extraction are difficult, it is hard to separate nearby vehicles, and there are more chances of occlusion.
- Despite the complexity of the problem, the algorithm needs to work fast. Although there is no real-time constraint, we still want a fast algorithm because we need to process a very large amount of video data.

We have developed three algorithms for vehicle tracking. The first approach [1] known as contour tracking, finds the boundaries (closed contours) between vehicles and the background, and dynamically tracks them. The second work [2] uses the background subtraction algorithm. The background is dynamically estimated from each incoming image, and the difference between the current and the background images is thresholded to form ``blobs'' corresponding to vehicles. This algorithm gives reliable vehicle location given a good illumination condition and a camera angle. Example tracking result of this system is shown in Figure 4.

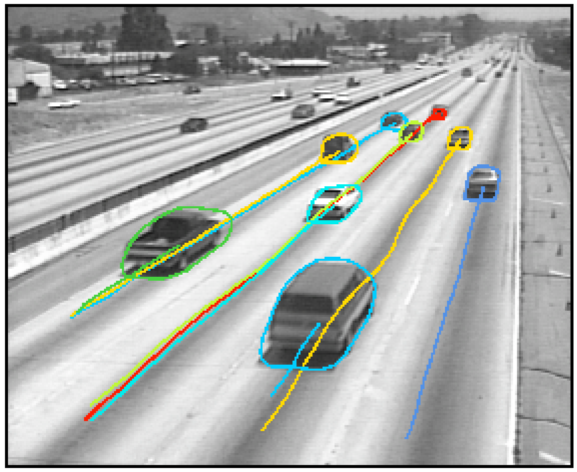

Figure 4. Vehicle Tracking -- Background Subtraction Algorithm

However, the performance of the background subtraction algorithms significantly degrades in the presence of heavy shadows. It is difficult to separate a shadow from the vehicle because the shadow moves along with the vehicle. Also, often, the shadow cast on nearby vehicles makes the separation between vehicles difficult. Background estimation is difficult when the traffic is heavy because 1) vehicle motion is small and 2) a significant part of the background is not observable.

Our third and current system, [3], [4], is based on corner feature tracking. In this system, vehicle trajectories are generated by grouping individually tracked corner features. **Figure 5** shows the flow diagram and **Figure 6** shows some of the intermediate results of the algorithm.

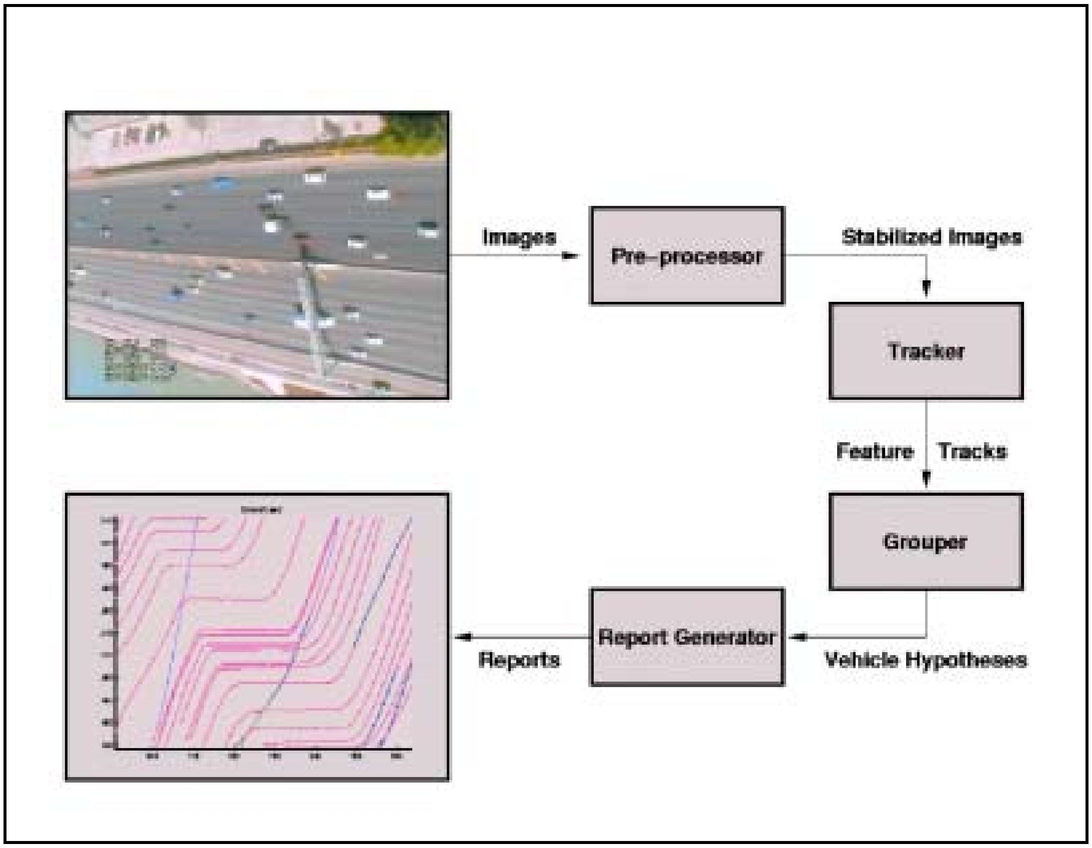

Figure 5. Flow Diagram of the Current System

(a) (b)

Figure 6. Intermediate Results of the Current Tracking Algorithm

The individual trajectories of the corners are shown in **Figure 6**a, and their grouping results are shown in **Figure 6**b.

The feature tracking algorithm has performed quite well in a variety of lighting and traffic conditions. The comparisons of the tracker output with human-generated ground truth show that in favorable conditions (light traffic and low shadow), one-to-one detection accuracy (one vehicle hypothesis matches to exactly one ground truth vehicle) exceeds 95%. Under less favorable conditions (heavy traffic, heavy shadow) this one-to-one accuracy is still better than 90% in most cases.

3.3 Multi-Sensor Traffic Data Fusion

The video and loop components of the BHL can be used together in two ways. First, one detection system can be used to verify another. An example of this is the use of video data to ground truth loop based vehicle re-identification algorithms (see [5]). Also, the two sensor systems can also be combined in a synergistic manner to exploit the strengths of each. For example, video can provide accurate speed measurements throughout the entire field of view. But due to partial occlusion, shadows, etc., it is difficult to segment 100 percent of the vehicles in a video stream. On the other hand, the loop detectors in the BHL provide very accurate passage information at discrete points. These vehicle passages can then be followed through the velocity field (t,x,y) to reconstruct individual vehicle trajectories.

4. RESULTS

We show some of the preliminary results from the ongoing data processing and analysis. Further information is provided in [4] and [5]. Figure 7 shows sample vehicle trajectories as a shock wave passes through the surveillance region. The tracker output is shown in solid lines and the manually generated ground truth is shown in dashed lines. Travel time estimation is shown in **Figure 8**. Measured link travel times over a 24 hour period for one lane of one link in the BHL are shown in **Figure 8**a, and the corresponding link densities are shown in **Figure 8**b. A measurement is made whenever a vehicle is re-identified at the downstream detector. The value is the quotient of the total number vehicles to pass the upstream detector during the period that the re-identified vehicle traversed the link divided by the length of the link.

5. CONCLUSIONS

We have completed the installation of a video surveillance system on I-80 in Emeryville, which is now successfully in operation. The coverage of the camera overlaps with the location of 8 loop detectors. We have collected video data of over 12,000 camera-hours, among which the loop detector results (of the same time) are also available. We have also presented some preliminary tracking results of our video-based algorithm. This project was focused on building a data collection infrastructure for our future in-depth research on the multi-sensor traffic data fusion. We have presented two ways of combining video and loop data, which we will focus on our ongoing and future research.

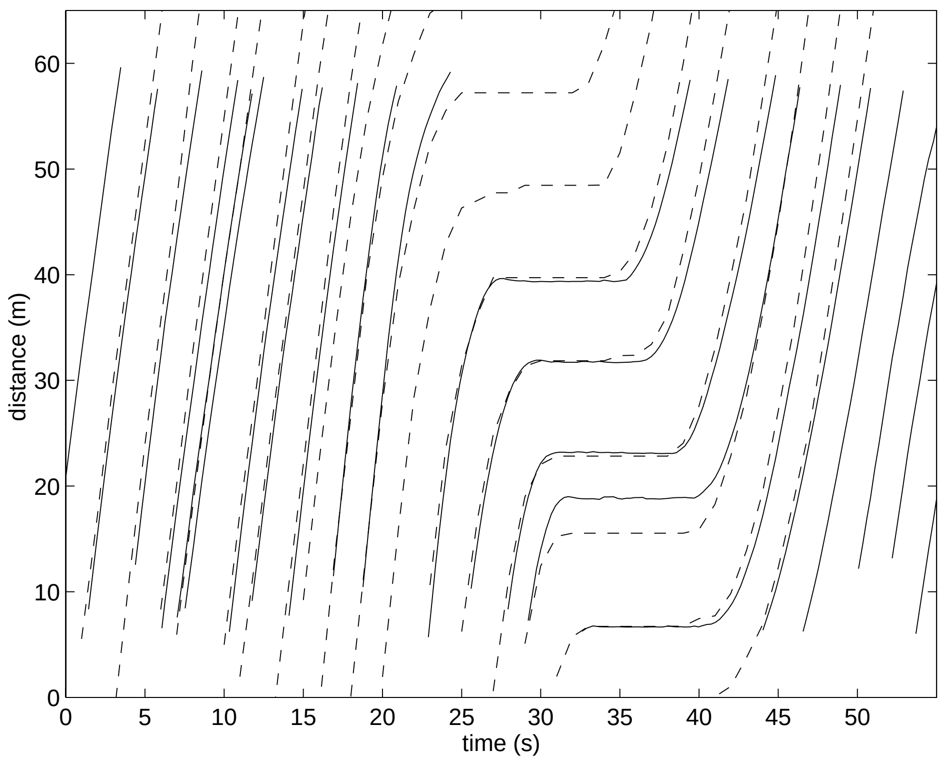

Figure 7. Comparison of Video Tracker and Manually Generated Vehicle Trajectories

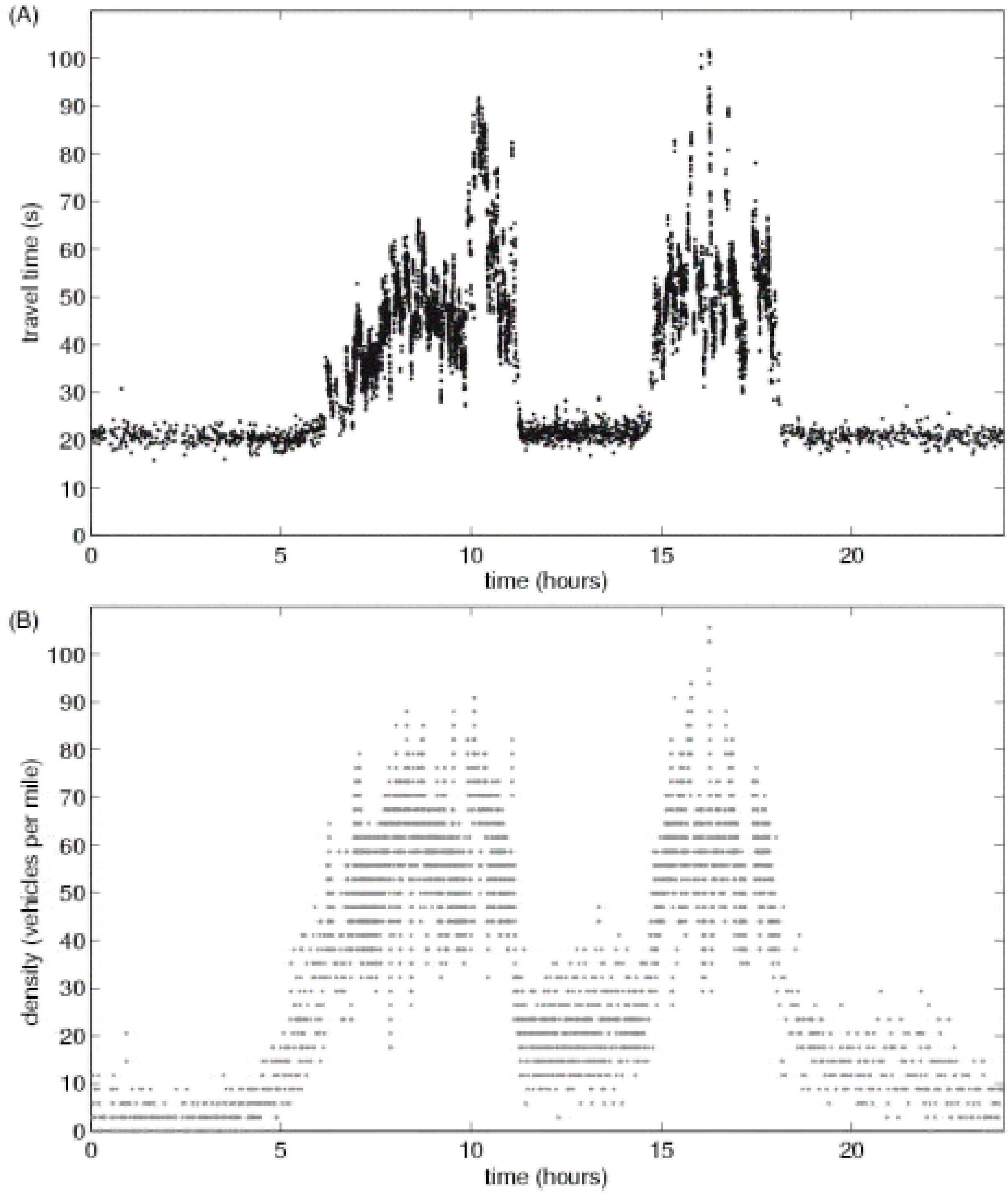

Figure 8. Travel-Time Estimation
(A) Measured Link Travel Times Over A 24 Hour Period for one Link
(B) The Corresponding Link Densities

REFERENCES

[1] D. Koller, J. Weber, T. Huang, J. Malik, G. Ogasawara, B. Rao, and S. Russell, "Towards robust automatic traffic scene analysis in real-time," *Proceedings of the 12th IAPR International Conference on Pattern Recognition*, Jerusalem, Israel, October 1994.

[2] D. Koller, J. Webber, and J. Malik, "Robust Multiple Car Tracking with Occlusion Reasoning," *Proceedings of European Conference on Computer Vision*, vol. A, pp. 189-196, 1994.

[3] D. Beymer, P. McLauchlan, B. Coifman, and J. Malik, "A Real-time Computer Vision System for Measuring Traffic Parameters," *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp. 495-501, 1997.

[4] Coifman, et al, 2000, "The Berkeley Highway Laboratory-Building on the I-880 Field Experiment," *Proceedings 3rd IEEE Conference on Intelligent Transportation Systems*, Detroit, October 2000.

[5] B. Coifman and E. Ergueta, "Improved Vehicle Reidentification and Travel Time Measurement on Congested Freeways", *ASCE Journal of Transportation Engineering*, to appear.