Traffic Surveillance with Wireless Magnetic Sensors

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ABSTRACT

Wireless magnetic sensor networks offer an attractive, low-cost alternative to inductive loops, video and radar for traffic surveillance on freeways, at intersections and in parking lots. The network comprises 5” diameter sensor nodes (SN) glued on the pavement where vehicles are to be detected. The SNs send their data via radio to the “access point” (AP) on the side of the road. The AP forwards sensor data to the Traffic Management Center via GPRS or to the roadside controller. Because such networks can be deployed in a very short time, they can also be used (and reused) for temporary traffic measurement. Vehicles are detected by measuring the change in the Earth’s magnetic field caused by the presence of a vehicle near the sensor. Two sensor nodes placed a few feet apart can estimate speed. A vehicle’s magnetic ‘signature’ can be processed for classification and re-identification. The paper describes the algorithms and presents experimental results comparing the accuracy of such a wireless sensor network with loop detectors and video.

KEYWORDS wireless sensors, traffic surveillance, vehicle classification, advanced traffic management systems.

1. INTRODUCTION

Wireless magnetic sensor networks offer a very attractive alternative to inductive loops for traffic surveillance on freeways and at intersections in terms of cost, ease of deployment and maintenance, and enhanced measurement capabilities. These networks consist of a set of sensor nodes (SN) and one access point (AP). A SN comprises a magnetic sensor, a microprocessor, a radio, and a battery. Each SN is encased in a 5”-diameter ‘smart stud’ container that is glued to the center of a lane.

A SN is a self-calibrating unit designed to process real time measurements and transmit useful data to the AP, located on the roadside, which is either line- or solar-powered The AP is housed in a 3”× 5” × 1” box attached to a pole or cabinet, which comprises a radio and a more powerful processor. Useful data collected from the SNs are then transmitted to a local controller or to the TMC. Figure 1 shows how such a network could be deployed.

Wireless sensing has the potential to revolutionize the way traffic data are collected, by providing measurements with high spatial density and accuracy. A network of wireless magnetic sensors offers much greater flexibility and lower installation and maintenance costs than inductive loop, video and radar detector systems. The suitability for large-scale deployment of such networks makes it possible to collect traffic data that are presently not available, but are needed to analyze and control a transportation system. The availability of these data opens up new opportunities for traffic operations and control.

The paper focuses on the extraction of information from experimentally obtained magnetic measurements. A sensor network implements two functions: detection and measurement, and communication. Communication is discussed in [1]. In this paper, we discuss the experiments and how well a magnetic sensor can detect vehicles and estimate various traffic parameters.

Five experiments are summarized. The first provides a two-hour trace of measurements at a local traffic site, downstream of a signalized intersection. A total of 793 vehicles are observed. The (correct) detection rate of the sensor network is 98% compared with 86% by the inductive loop. The second experiment was performed at a parking lot to study the detection of a stationary vehicle.

The third experiment gives a half-hour trace of speed estimates at a local traffic site. The speed estimates by the sensor nodes is more accurate than that using video, and the distribution of the vehicle magnetic lengths is consistent with that of the vehicle types.

The fourth experiment results in a four-hour trace of measurements at a Weigh-in-Motion (WIM) station in San Leandro, CA. Magnetic signatures from 265 trucks are classified into five FWHA classes. The algorithm achieves 80 percent correct classification in *real time*, *without* using vehicle length.

The fifth experiment is a preliminary study of the use of sensor networks for re-identification by. Four nodes are placed across a lane with three different test vehicles running over it repeatedly. The vehicle is always correctly re-identified even when the vehicle runs are not aligned.

Section 2 presents the results of the experiments for vehicle detection near the intersection and in the parking lot. Section 3 compares the speed estimates by the sensor nodes and video, as well as the magnetic length distribution of the cars obtained by these speed estimates. Sections 4 and 5 explore the classification and the re-identification of vehicles based on magnetic signatures. Section 6 discusses the results and outlines future work. Section 7 concludes the paper.

2. VEHICLE DETECTION

Data were collected from a single sensor node placed in the middle of an inductive loop in one lane on Martin Luther King Blvd., Berkeley, CA, on October 4, 2004, 1-3 pm.

Ground truth was established by visual count from the recorded video. In all 793 vehicles were observed: Passenger vehicles (466); Wagons (41); SUVs (87); Vans (82); Pickup (87); Trucks (26); Buses (2); and Motorcycles (2).

The node has a correct detection rate of 98% (8 overcounts and 7 undercounts out of 793 vehicles). The inductive loop has a correct detection rate of 86% (111 *net* overcounts out of 793 vehicles; it was not possible to separate loop undercounts and overcounts).

The sensor measures *mag(z)*, the magnetic field in the vertical direction, and *mag(x)*, the magnetic field in the direction of the movement of the vehicle, sampled at 128Hz. The *mag(z)* signal is compared with a threshold, resulting in a sequence of 1's and 0's. If 10 successive values are 1 (above the threshold), vehicle detection is declared. When the signals for both *mag(z)* and *mag(x)* subsequently fall below the threshold for 0.25s, the vehicle is declared to have passed the sensor. The state machine coded in the SN processor sets a detection flag whose value is 1 for the time during which a vehicle is above the sensor, and whose value is 0 otherwise. Figure 2 displays the raw samples (left) of *mag(z)* from the passage of a single vehicle and the corresponding detection flag (right).

The second experiment was performed at a parking lot on Hearst Avenue, on February 16, 2005. Four sensor nodes were placed along the middle of a target parking slot. Figure 3 displays plots of *mag(x)*, *mag(z)* and *mag(y)*, the magnetic field in the direction perpendicular to the movement of the vehicle, and the detection flag of two of the nodes, one in the middle and the other at the end of the parking space. A test vehicle was first parked in the left parking slot, then on the target slot and finally on the right slot. Since the magnetic field change decays rapidly with distance, the vehicle is not detected when it is parked to the adjacent slot (This feature is also used to distinguish vehicles in different lanes on the road). The detection algorithm is basically the same as that in the first experiment. The only difference is that the sensor is not allowed to re-calibrate itself even the detection flag stays high for a very long time in the parking space.

3. VEHICLE SPEED AND MAGNETIC LENGTH ESTIMATION

Two sensor nodes were glued six feet apart, along the middle of a lane on Hearst Avenue, Berkeley, CA, on April 19, 2004. Figure 4 shows the z-axis measurements of the nodes together with the detection flag from the threshold based detection algorithm. The speed of the vehicle is estimated as the ratio of the distance between the sensor nodes to the difference between the downtimes of the detection flags. The sources of error in this estimation are the synchronization errors and the different sensitivity of the sensors.

Two cones were placed 22.6' apart on the site to be used as landmarks for video processing. We compared the speeds estimated by the sensor nodes and using the video. Summary statistics of the speeds estimated by the two methods are shown in Table 1, and the scatter plot of the speed estimates is shown in Figure 5. The overall statistics of the estimates from the two methods agree. Since the sampling rate of the magnetometer is 128Hz while the video frame rate is only 30Hz, the video estimates are less accurate and have a positive bias., even though the landmarks for the video are much further apart than the sensor nodes.

The *on-time* or interval between successive uptime and downtime of the detection flag is the time during which a vehicle is above the sensor. Once the speed of the vehicles is found, the magnetic length of the vehicle is given by the product of its on-time and its speed. (The ratio of on-time to total time is the occupancy.) Figure 6 shows the distribution of the estimated magnetic length, which is consistent with the distribution of the vehicle types observed.

4. VEHICLE CLASSIFICATION

Classification of *individual* vehicles requires finer measurements. This section reports the results of a simple classification scheme based on a magnetometer that measures the earth's magnetic field along the direction of motion (*mag(x)*), perpendicular to the motion (*mag(y)*), and in the vertical direction (*mag(z)*), each sampled at 128Hz.

We called this simple scheme "Hill Patterns Classification". It may not be the best in terms of correct classification rate, but it is simple enough to be implemented by the microprocessor in the sensor node in real time.

A vehicle's magnetic *signature* is processed and two pieces of information are extracted. First, the rate of change of consecutive samples is compared with a threshold and declared to be +1 (–1) if it is positive and larger than (negative with magnitude larger than) the threshold, or 0 if the magnitude of the rate is smaller than the threshold. The result is a '*hill pattern*' of 'peaks' and 'valleys' in the vehicle's signature. The second piece of information is the magnetic length of the vehicle. A simple algorithm uses this information to classify the vehicle into five types: FWHA index 5,6,8,9 and 11.

The fourth experiment provides a four-hour trace of measurements at a Weight-in-Motion station in San Leandro, CA. The magnetic signatures of 256 trucks were collected. Speed estimates were obtained by a node pair as described in section 3; the speed estimate is used to obtain magnetic length. Ground truth is obtained from visual classification, based on the video recording.

Figure 7 displays the magnetic signatures and hill patterns from two class 5 trucks. There are six plots per vehicle. The left column shows the magnetic signals from each of the three axes: *mag(x), mag(y)* and *mag(z).* The right column shows the corresponding hill patterns. Figure 8 displays the signature, hill pattern and classification of two trucks of class 9.

Table 2 shows the correct classification rates of the hill patterns scheme using different features. It indicates that 82% of 265 vehicles are correctly classified when the hill patterns of all the three axes and magnetic length are used. Surprisingly, even if the magnetic length is *not* used, the classification rate is above 80%. Unlike classification schemes proposed in [2], the "hill pattern" classification can be carried out in real time, with very little processing.

The sensor node uses the HMC 1051Z Honeywell chip, whose magneto-resistive sensors convert the magnetic field to a differential output voltage, capable of sensing magnetic fields as low as 30 micro-gauss [11]. (The earth's field is between 250 and 650 milliGauss.) Ferromagnetic material, such as iron, with a large permeability, changes the earth's magnetic field. The voltage change is sampled at 128Hz to give the signature. By contrast, the inductive loop is an active device: a 6' by 6' copper loop is excited by a 20kHZ voltage, creating a magnetic field. Conducting material passing over the loop lowers the inductance. The loop detector card measures the change in the inductance. Special high scan-rate detector cards used for vehicle classification sample the inductance at about 140Hz.

The tiny magnetic sensor measures a highly localized change. As the vehicle travels over the sensor, it records the changes in the magnetic fields caused by different parts of the vehicle. By contrast, the 6' by 6' standard loop geometry results in the "integration of the inductive signature over the traversal distance … which can *remove distinctive features* from the inductive signature" [4, emphasis added]. So the standard loop is not ideal for vehicle classification. Magnetic signatures from magnetometer provide much more detail.

5. VEHICLE RE-IDENTIFICATION

Vehicle re-identification techniques can be employed to estimate turning movements at an intersection or roundabout, and to estimate travel times. Vehicle re-identification techniques match the signature of the vehicle at a downstream sensor node with the vehicle's corresponding signature at an upstream sensor node.

Four sensor nodes were placed on a lane in Richmond Field Station, Richmond, CA, on February 23, 2005, as shown in Figure 9. Five sets of data are recorded for each of the three test vehicles: Toyota Tercel, Toyota Camry and Ford Taurus. The speed determined by a node pair is used to normalize the magnetic signatures of the vehicles. One run of each vehicle is recorded as a test signature. Each subsequent run of any vehicle is correlated with each test signature, and the vehicle whose test signature gives the maximum correlation is declared to be the detected vehicle. The correct detection is made each time. Note that the different runs of the same vehicle are *not* aligned relative to the sensor nodes.

6. DISC USSION AND FUTURE PLANS

The limited experiments reported here suggest that a magnetic sensor provides count accuracy exceeding 98 percent, and two magnetic sensors achieve better vehicle speed estimates than video. Further, a tri-axis magnetometer can classify five classes of truck with accuracy over 80 percent.

An earlier study [1] described a communication protocol that consumes so little power that a sensor node can be supplied by energy from two AA batteries for more than three years. More careful designs by Sensys Networks, Inc. indicate a lifetime exceeding seven years. (Full disclosure: Pravin Varaiya is a founder of Sensys.) The low-cost, ease of deployment and maintenance, and more detail information provided by these sensor networks, suggest that they can serve as a foundation for an accurate, extensive, and dense traffic surveillance system.

In the future, we plan to work in several directions. We will conduct tests on freeways for vehicle detection, classification, speed estimation and re-identification. We also plan to conduct experiments on bridges and overpasses, where it is difficult to cut the pavement to install loop detectors. The absence of detectors at these locations (where congestion often occurs) leaves a significant gap in traffic monitoring.

Over the longer term, we will explore other sensing modalities, including temperature and fog sensors, and accelerometers. The interesting thing about the wireless network (figure 1) is that the same communication and node architecture can be used to process and communicate measurements from different sensors.

The PeMS system [12] has shown the value of traffic data for measuring and improving freeway performance. PeMS also shows how difficult it is to maintain California's loop detector system. Wireless sensor networks may provide the ideal low-cost, accurate traffic surveillance system needed to improve our transportation system.

7. CONCLUSIONS

Vehicle detection systems based on wireless sensor networks are attractive because of their low cost, ease of installation and flexibility of deployment. The paper examined their detection capability at urban street intersections and parking lots. The networks provide a detection rate of 98 percent; and achieve 90 percent accuracy in average vehicle length and speed estimates. The localized change associated with the magnetic sensor allows us to classify the vehicles based on the magnetic signature with 80 percent accuracy. In the future, we plan to continue to work on the classification of the vehicles and different kinds of trucks, and perform extensive experiments on urban streets and freeways with multiple lanes and higher volumes.

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Figure 1 Deploying sensor networks at freeway (left), intersection (middle), and parking lots (right)

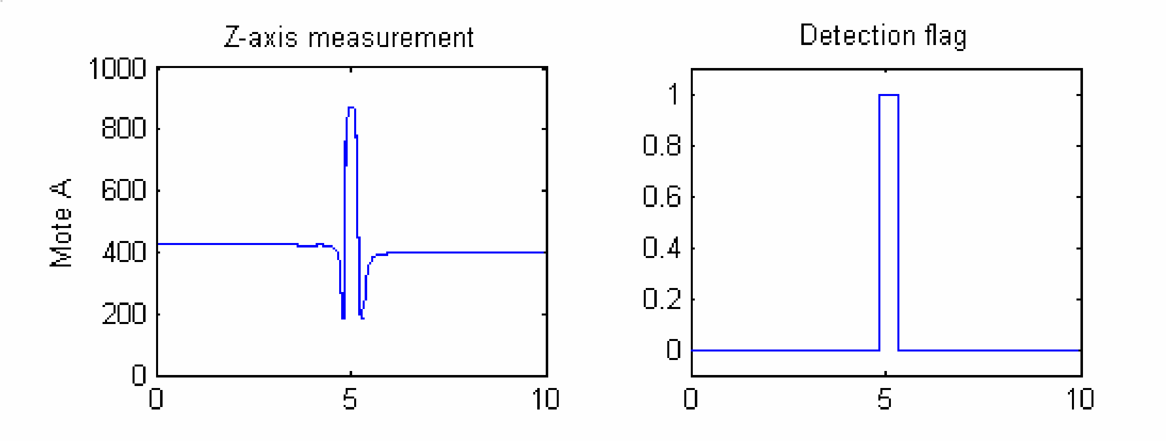

Figure 2 Raw samples of *mag(z)* and detection flag of a sensor node near an intersection; time (x-axis) is in seconds

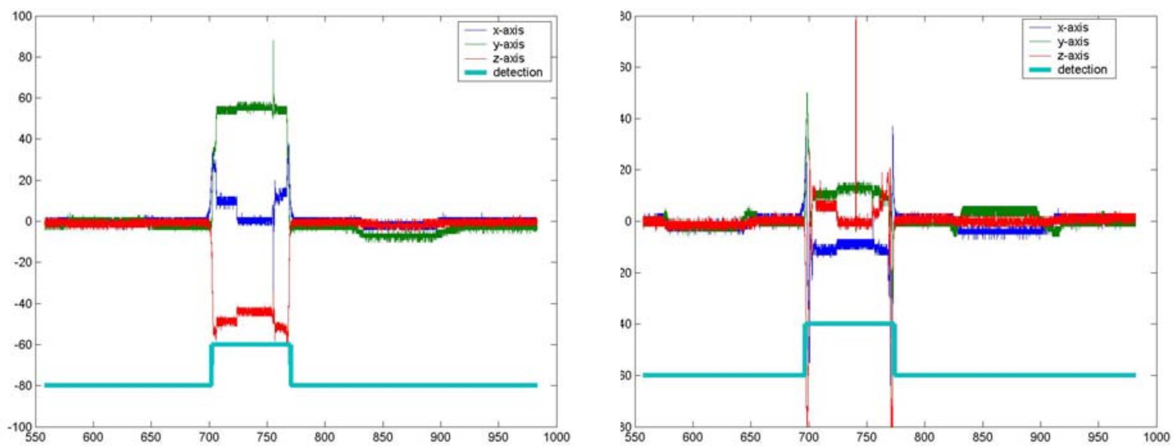

Figure 3 Raw samples of *mag(x)*,*mag(y)*, *mag(z)* and detection flag of the sensor node in the middle (left) and end (right) of the parking space; time (x-axis) is in seconds

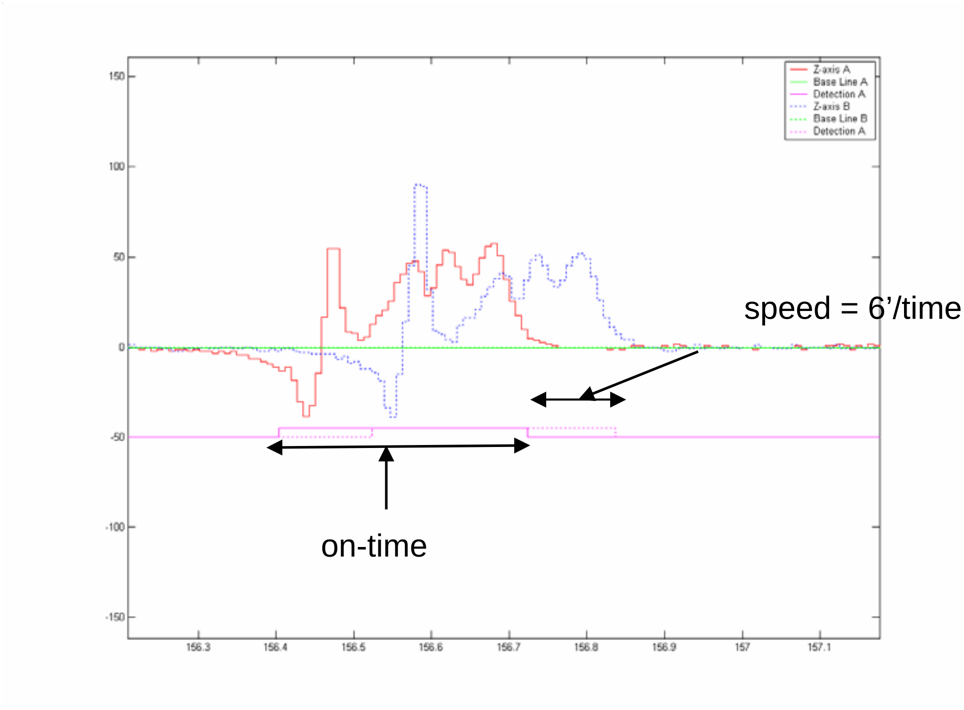

Figure 4 Determining speed based on the magnetometer signals of two sensor nodes

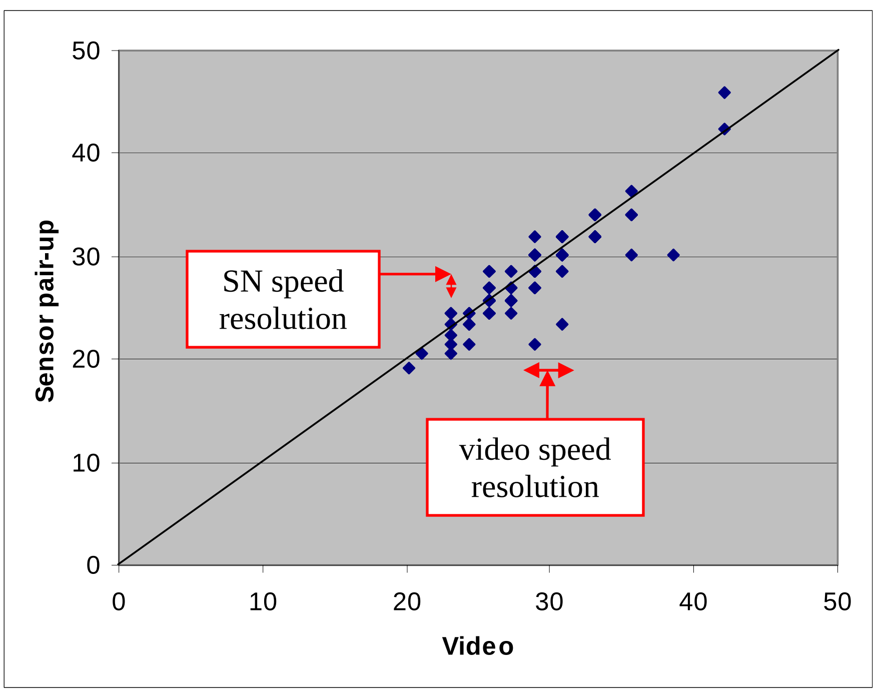

Figure 5 Comparison of speeds determined by two sensor nodes and the video

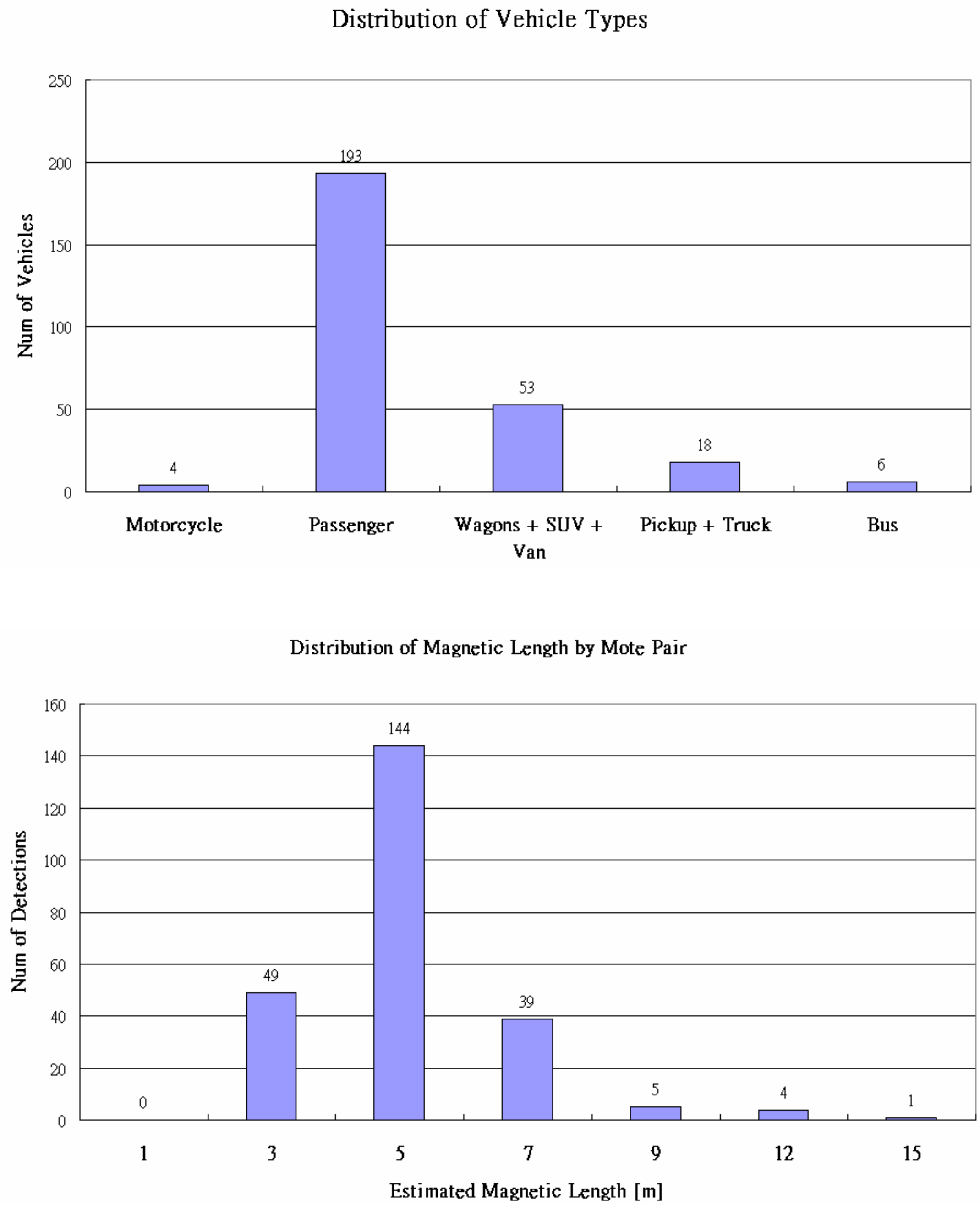

Figure 6 Distribution of vehicles types and estimated magnetic length by a node pair

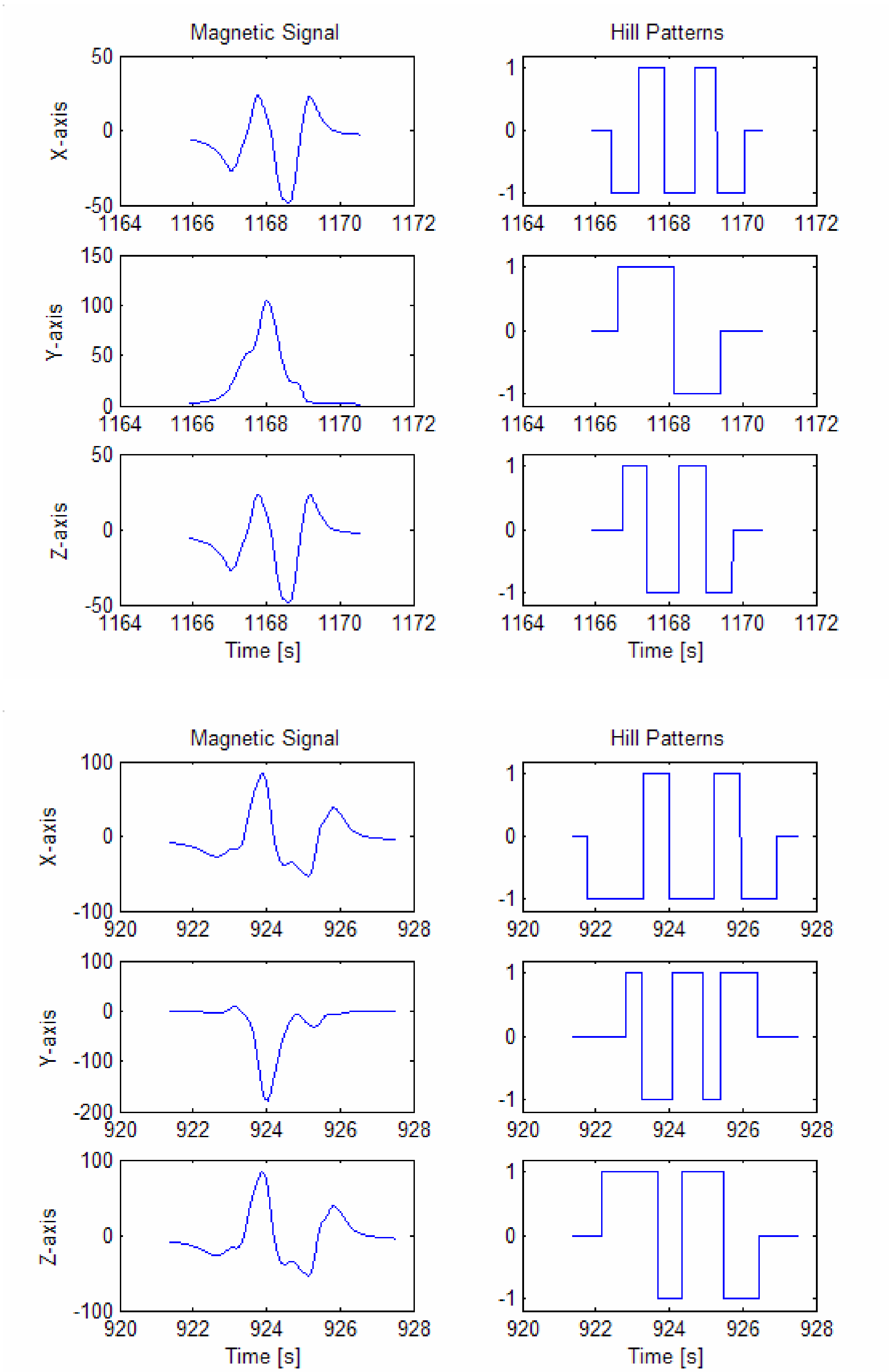

Figure 7 Magnetic signals and hill patterns from two trucks of FWHA class 5

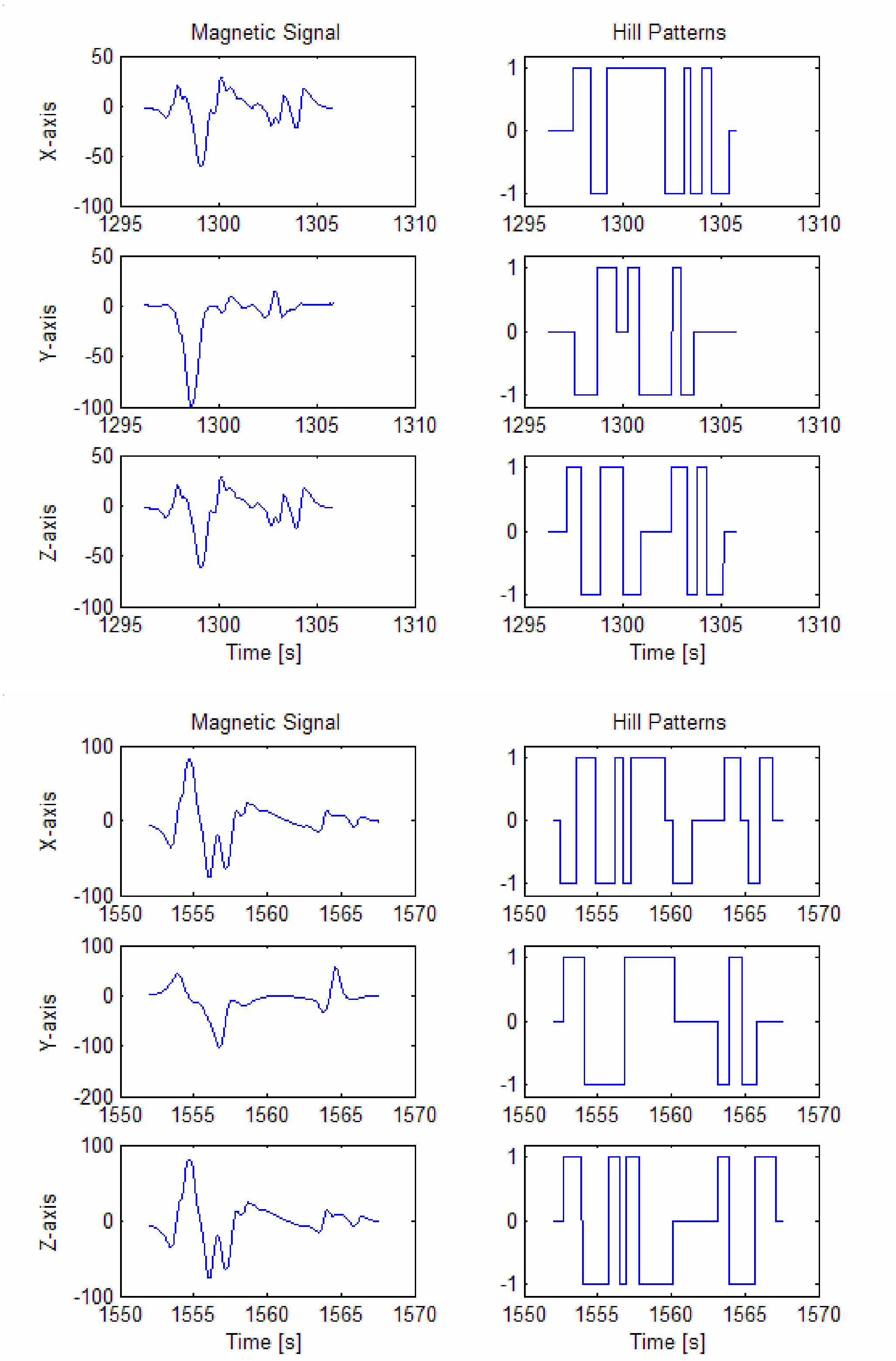

Figure 8 Magnetic signals and hill patterns from two trucks of FWHA class 9

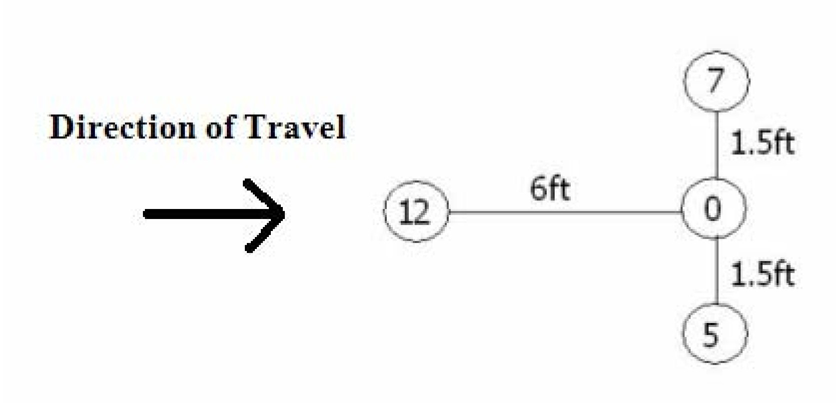

Figure 9 Configuration of the nodes for re-identification experiment

Table 1 Comparison of estimated speeds from a sensor node pair and video

Statistic	Video (mph)	SN (mph)
Average	29.2	28.8
Minimum	20.1	19.1
Maximum	46.3	46.0
Median	28.9	28.5

Table 2 Classification results by hill patterns scheme

Features	Correct Classification %
X-Hill and Magnetic Length	53.21
Y-Hill and Magnetic Length	62.64
Z-Hill and Magnetic Length	59.25
XYZ-Hills	81.51
XYZ-Hills and Magnetic Length	82.64