SenseMag: Enabling Low-Cost Traffic Monitoring Using Noninvasive Magnetic Sensing

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***Abstract*—The operation and management of intelligent transportation systems (ITS), such as traffic monitoring, relies on real-time data aggregation of vehicular traffic information, including vehicular types (e.g., cars, trucks, and buses), in the critical roads and highways. While traditional approaches based on vehicular-embedded GPS sensors or camera networks would either invade drivers' privacy or require high deployment cost, this article introduces a low-cost method, namely, *SenseMag*, to recognize the vehicular type using a pair of noninvasive magnetic sensors deployed on the straight road section. *SenseMag* filters out noises and segments received magnetic signals by the exact time points that the vehicle arrives or departs from every sensor node. Furthermore, *SenseMag* adopts a hierarchical recognition model to first estimate the speed/velocity, then identify the length of the vehicle using the predicted speed, sampling cycles, and the distance between the sensor nodes. With the vehicle length identified and the temporal/spectral features extracted from the magnetic signals, *SenseMag* classifies the types of vehicles accordingly. Some semiautomated learning techniques have been adopted for the design of filters, features, and the choice of hyperparameters. Extensive experiment based on real-word field deployment (on the highways in Shenzhen, China) shows that *SenseMag* significantly outperforms the existing methods in both classification accuracy and the granularity of vehicle types (i.e., seven types by *SenseMag* versus four types by the existing work in comparisons). To be specific, our field experiment results validate that *SenseMag* is with at least 90% vehicle type classification accuracy and less than 5% vehicle length classification error.**

***Index Terms*—Internet of Vehicles (IoV), magnetic sensing, traffic monitoring, vehicle-type classification.**

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I. Introduction

With the rapid development of ubiquitous sensing, communication, and computing devices, smart cities with intelligent transportation systems (ITS) [1] are conforming to new standards and requirements of modern urbanization and civilization. The smart operation and management of ITS, such as the monitoring of urban traffic safety, relies on real-time data aggregation of vehicular traffic information in the critical roads and highways of the city. For example, to smooth the urban traffic in rush hours, ITS frequently encourages passengers to share drives in certain roads/slots through car pooling. To specify the roads for car pooling, ITS needs to measure the traffic volume, vehicular type (private cars or public buses), and traffic status of each key road in the rush hours. While the traffic status (e.g., congested/jammed/smooth) can be identified by the speed of vehicles, there thus needs a method to identify and do statistics on the vehicular types and the traffic speed on the roads [2].

Generally, we can categorize the existing methods to obtain aforementioned information in two folders: 1) infrastructure-based approach [3], [4] and 2) infrastructureless approach [5], [6]. To build an infrastructure for traffic monitoring, the traditional method is to use camera array networks, where a large number of cameras are deployed to sense every corner of the streets/roads/highways to visually track each moving vehicle. They can localize each vehicle, identify its type, and measure its speed all using computer vision techniques. In terms of the infrastructureless approach, one can obtain the information about the vehicular type and speed using vehicular-embedded GPS sensors in a so-called crowdsensing manner [7]–[9]. For example, some navigation Apps [6], [10] on smartphones would first require drivers to input their personal information, then track their real-time mobility, including GPS location and speed. With the large-scale GPS tracking and data aggregation, one can easily map and update the statistics on the vehicular types and speed

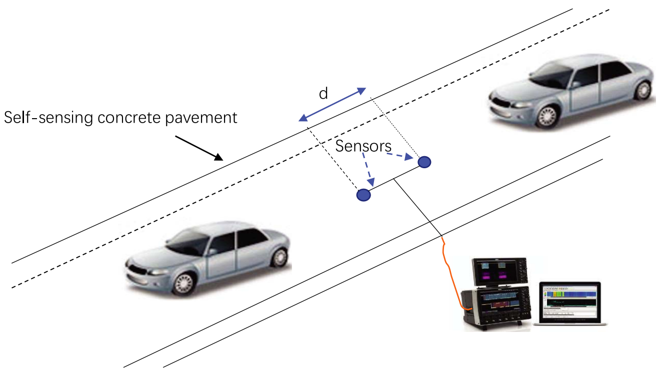


Fig. 1. Deployment of magnetic sensors for traffic monitoring. (Specifically, *SenseMag* adopts two magnetic sensors to gather information.)

onto each road of the city in real time. Note that a GPS-based solution no longer works when the user turns off the mobility tracking, while the deployment of camera networks relies on the huge monetary investment. Furthermore, both existing infrastructure-based and infrastructureless techniques would invade the privacy of drivers. All the above issues would burden the scalability of traffic monitoring. Thus, a low-cost method is needed to obtain the vehicular type and speed in real time without seriously invade users' privacy [11].

Among a wide range of approaches, magnetic sensors can identify the vehicular types and measure the speed without tracking each individual users' mobility in an noninvasive manner [12]–[19]. Fig. 1 demonstrates a typical deployment of magnetic sensors for traffic monitoring. Prior to the traffic monitoring, a magnetic sensing system that can detect the change of surrounding magnetic fields has been already deployed on/under the surface of the highway. Specifically, any approaching vehicle can be viewed as a moving magnet that would cause slight perturbation in the surrounding magnetic field. In this way, per vehicle approaching, the magnetic sensing system would be activated by the change of the magnetic field and start to collect magnetic field signals for further processing and recognition. For example, Fig. 2(a) presents the magnetic signals with various approaching vehicles, where the magnetic signals are represented as the changes/trends of output voltages of the magnetic field sensors over time (in milliseconds). We could observe the patterns of signals and their difference for various vehicle types. With the collection of labeled data, such as clips of magnetic signals recorded with the identified vehicular types and speed, one can use general-purpose supervised learning techniques to identify the vehicles and classify the vehicular type. Such a method works but is with poor performance.

To categorize vehicles by their types, such as Sedan and SUV, Bus, and Light/Medium/Heavy/Super Truck, there frequently needs information on two attributes—the length of vehicles and the number of axles [20], [21]. Table I presents the standard range of vehicle lengths and the number of axles proposed by the Transport Planning and Research Institute (TPRI) [21], Ministry of Transport, China. To identify the length of a vehicle using magnetic signals, one usually needs to first predict the speed of the vehicle, which could be estimated using the time shift between the signals collected by the two sensors and the distance between the two sensors [22]. With the speed predicted, the length of the vehicle could be estimated by obtaining the time spent by the vehicle for driving through the sensor node from nose to tail.

TABLE I
VEHICLE TYPES AND THE STANDARD RANGES OF VEHICLE LENGTHS IN CHINA

Vehicle Type	Length Interval (m)	Axles
Motorbike	$(0, 3]$	0
Sedan, SUV	$(3, 6]$	2
Light truck	$(3, 6]$	2
Medium truck	$(6, 12]$	2
Bus	$(6, 12]$	2
Heavy truck	$(6, 12]$	3 or 4
Super truck	$(12, 20]$	4 or more

With the vehicle length estimated, according to Table I, one could categorize vehicles into four types in a coarse-grained manner. To push the resolution of vehicle-type classification, one could use supervised learning based on the collection of labeled signals. However, the aforementioned solution is with significant limitations as follows: 1) from the raw magnetic signals illustrated in Fig. 2(a), the exact time points that the vehicle arrives and departs from the sensor node are not obvious, and it is difficult to estimate the time spent by the vehicle for driving through the sensor node and 2) no matter from the temporal or frequency domains [shown in Fig. 2(b)], the raw signals are less discriminability, and it is difficult to learn classifiers based on these signals. Thus, there needs methods to process the signals to shape the vibration of magnetic fields caused by the passing vehicles and select discriminative features for vehicle type classification.

Contributions: In our research, we propose *SenseMag*, which intends to classify the vehicular type through magnetic sensing, signal processing, and semiautomated learning. Specifically, *SenseMag* filters out noises and segments received magnetic signals by the exact time points that the vehicle arrives or departs from every sensor node. Furthermore, *SenseMag* adopts a hierarchical recognition model to first estimate the speed/velocity, and later identify the length of vehicle using the predicted speed and the distance between the sensor nodes. With the vehicle length identified and the temporal/spectral features extracted from the magnetic signals, *SenseMag* classifies the types of vehicles accordingly.

Compared to the general-purpose magnetic approaches, with a collection of labeled signals, *SenseMag* adopts several semiautomated learning techniques for the design of filters, features, and the choice of hyper-parameters via the comparison of cross-validation accuracy. Some examples of signals processed by *SenseMag* (through interpolating, normalizing, and bandpass filtering) are illustrated in Fig. 2(c) and (d). In Fig. 2(c), we could clearly observe the time duration that the vehicle drives through the sensor node from the processed signals in temporal domain. Furthermore, Fig. 2(d) shows the discriminability of processed signals in both temporal/frequency domains by the vehicle types. We have made at least the following three contributions.

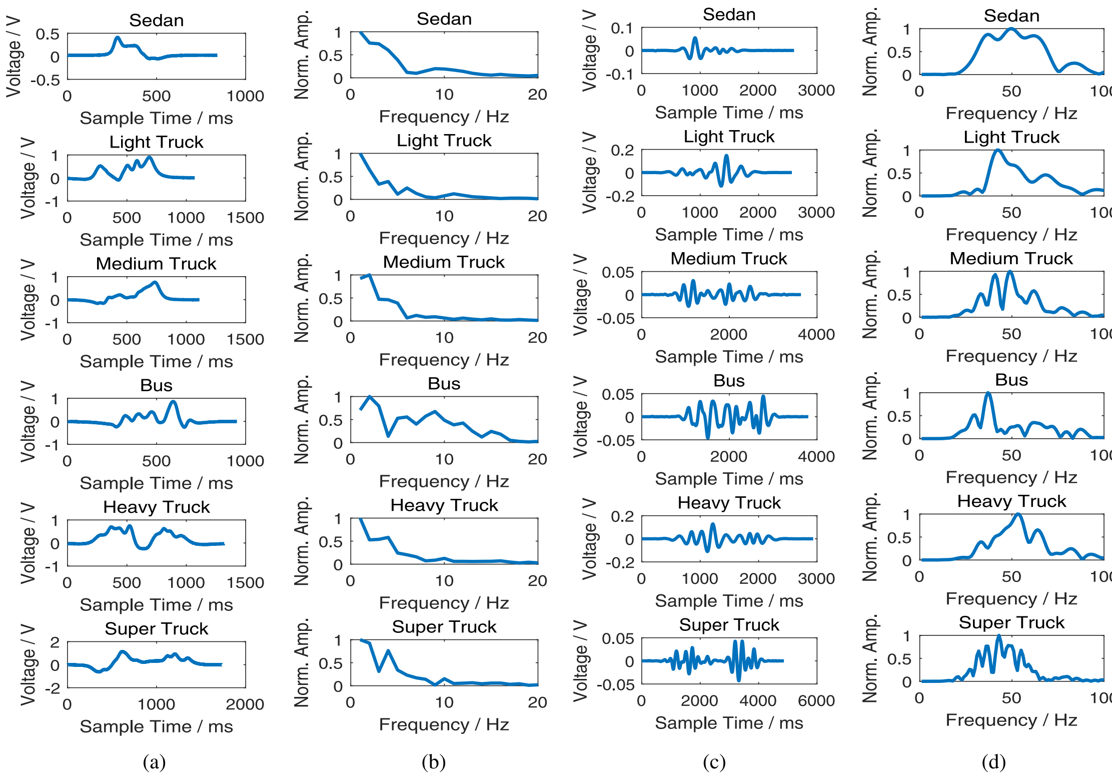


Fig. 2. Magnetic signals in temporal and frequency domains (the detailed way that we process the signal representations in the frequency domain will be introduced in Section IV-B). (a) Original temporal. (b) Original frequency. (c) Processed temporal. (d) Processed frequency.

1) We study the problem of vehicular traffic monitoring using magnetic field sensors, where we focus on vehicular-type classification and traffic speed prediction using received magnetic field signals. To the best of our knowledge, it is the first work that aims at identifying the type of vehicles by measuring the speed and categorizing the vehicle lengths using a pair of magnetic sensors deployed on the straight section of highways, by tuning the performance of signal processing and recognition through semiautomated learning.
2) We propose *SenseMag*—a magnetic sensing system with a hierarchical recognition model using a set of learning algorithms that can predict the traffic speed, identify the vehicle lengths, and classify the vehicular types accordingly. Specifically, *SenseMag* adopts denoising treatments to extract waveforms from raw signals, and match the signals collected by the two sensors through maximizing correlation coefficient between the two signals with a time shift. With the time shift estimated, *SenseMag* predicts the speed/velocity of the vehicle with respect to the sampling rate of magnetic sensors and the distance between the two sensors. Later, *SenseMag* filters out the noises from normalized signals in a bandpass fashion with respect to the predicted speed, and estimates the length of vehicle using a parameterizable white-box model. With a collection of labeled signals, *SenseMag* tunes parameters of low-pass/high-pass filters as well as the hyperparameters for length estimation through semiautomated learning via the comparisons of cross-validation accuracy. Finally, *SenseMag* classifies the type of vehicle using the predicted length and temporal/frequency-domain features extracted from signals.
3) We conduct extensive experiments based on real-world field deployment—four *SenseMag* systems deployed on the highways in Shenzhen, China. The experiment results show that *SenseMag* can accurately identify the vehicular length and type; specifically, *SenseMag* is with at least 90% vehicle-type classification accuracy with less than 5% vehicle length classification error. *SenseMag* can clearly outperform the existing systems [17]–[19] in both classification accuracy and the number of recognizable vehicle types (seven types by *SenseMag* versus four types in [17]–[19]), while the deployment cost of *SenseMag* is extremely low.

II. Related Works and Discussion

In this section, we review the relevant works in vehicle speed estimation, vehicle length estimation, and the vehicle-type classification using magnetic sensors.

A. Related Works

Magnetic sensing has been used in vehicular traffic surveillance [12]–[15], including detecting vehicles, estimating speed of vehicles, reidentify vehicle, and classifying the vehicle types. Incorporating anisotropic magneto-resistive (AMR) signals measured from magnetic, Caruso and Withanawasam [12] proposed to use AMR signals to classify vehicle types, including cars, vans, trucks, buses, trailer trucks, etc. The use of either single or multiple magnetic sensors has been studied in [23], where multisensor fusion for magnetic sensing has been used for vehicle-type classification. Furthermore, various approaches have been studied to use magnetic sensing to classify the types of vehicles, such as [24]–[31].

In addition to classification, vehicle tracking refers to monitoring the transient status of a moving vehicle. To achieve the goal, magnetic dipole models have been used and studied in [19], [23], and [32]–[35], where variations of magnetic fields caused by the moving objects have been measured by magnetic sensors to track the vehicles. In addition to speed measurement, passing vehicle counting has been studied in [36]–[45], where the wave pattern matching of magnetic signals has been adopted in the algorithms.

More specifically, Kaewkamnerd *et al.* [45] proposed to use some advanced features that could be obtained in low complexity, to achieve better classification accuracy for small vehicles. These features, including Average-Bar, Hillpattern peaks, and magnetic signal differential energy, have been normalized to predict the vehicle speed and length. Furthermore, one could first measure the vehicle speed, then identify the vehicle length, and use the vehicle length as the feature to classify vehicle types [46]. Novel millimeter-based Vehicle-to-Vehicle (VoV) and Vehicle-to-Infrastructure (VoI) communication techniques could be used to improve the overall performance of traffic monitoring [47]. Note that the performance evaluation and measurements in the above work are all based on their own settings of deployments/experiments, which usually are not comparable with each other.

B. Discussion and Comparisons to Our Work

The most relevant studies to our work are [17], [19], and [48]. Particularly, [17] proposed a portable roadside magnetic sensors for vehicle-type classification, where they tried to classify vehicles into four types with the classification accuracy of 83.62%. Specifically, they use the Hill-Pattern, Peak-Peak, Mean-Std, and Energy as features. Various supervised learners, including the K-nearest neighbor (KNN), support vector machine (SVM), and backpropagation neural network (BPNN) have been used for classification. Velisavljevic's system [48] could achieve a classification accuracy rate of 88.37% with five vehicle classes when it was evaluated on a large realistic data set. While all the above works use common statistical learners, such as SVM, BPNN, KNN, K-means, perceptron neural network, etc., using handcraft features extracted from either temporal/frequency domains, our work adopts automated machine learning [49]–[52] that searches the empirically best classifiers with fine-tuned features and hyperparameters to obtain the decent accuracy.

Despite the work [17], [48] achieves high recognition rate (88.37% and 83.62%), their method has the following limitations: 1) it does not solve the problem of noise on the frequency waveform and 2) the extracted features from the frequency waveform are not adequate to obtain all the distinctive properties of the vehicles. Generalization performance of the existing classification work may be affected by too little realistic data. The proportion of vehicle type in the existing

TABLE II
NOTATIONS FOR *SenseMag*

Notations	Meaning
d	Two sensors distance
f	ADC frequency of pre-processor
$\boldsymbol{x}'$	Original signal vector from the first sensor
$\boldsymbol{x}''$	Original signal vector from the second sensor
$\boldsymbol{x}$	Bandstop filterd signal vector for $\boldsymbol{x}'$
$\boldsymbol{x}^{norm}$	Interpolated normalization for original signal vector
$\boldsymbol{x}^{lh}$	Lowpass and highpass filtered signal vector for $\boldsymbol{x}^{norm}$
$\boldsymbol{X}$	Frequency domain signal vector for $\boldsymbol{x}^{norm}$
$\boldsymbol{X}^{norm}$	Normalize frequency domain signal vector $\boldsymbol{X}$
$\boldsymbol{X}^{low}$	Low frequency of truncated vector $\boldsymbol{X}^{norm}$
$\boldsymbol{F_s}$	Chebyshev type I bandstop filter
$\boldsymbol{F_l}$	Butterworth lowpass filter
$\boldsymbol{F_h}$	Butterworth highpass filter
τ	Cross-correlation translation
v	Velocity of vehicle
L^0	Real length of vehicle
L	Length of vehicle

work data set is far away to most country roads or urban road. Heuristically, speed and length of the vehicle are those of the most important features that the magnetic sensor can detect precisely. The length can be used to classify some vehicles in big classification. Our work is the first to use magnetic sensing measure vehicle speed and length for big classification, then use integral features of the time–frequency domain to get higher vehicle classification. Only using two sensors is another advantage of our solution. This design simple and robust. The most recent work, MagMonitor [19], introduces multiple magnetic dipole models. They propose to measure the magnetic signals from three orthogonal directions (x, y, z) in the space, while our work only uses the magnetic signals in the z direction while achieving better accuracy in recognition.

III. *SenseMag* SYSTEM DESIGN

In this section, we first introduce the architectural design of *SenseMag* with details of systems implementation. The notations used for SenseMag are listed in Table II.

A. Overall Architectural Design

Fig. 3 illustrates the architectural design of *SenseMag*. The purpose of *SenseMag* is to provide real-time vehicular information to a central ITS server. More specifically, *SenseMag* follows a master–slave design pattern with a hierarchical structure, where

1) a centralized processor is used to collect and aggregate sensing data from multiple parallel preprocessors and uploads the aggregated results to the central server;
2) every preprocessor is connected to two magnetic sensors deployed on the road and the two magnetic sensors could capture the necessary magnetic signals for vehicle speeding detection, length estimation, and the type classification.

In this way, an ITS server could be deployed to monitor a large transportation system with road networks using multiple nodes (preprocessor and magnetic sensors).

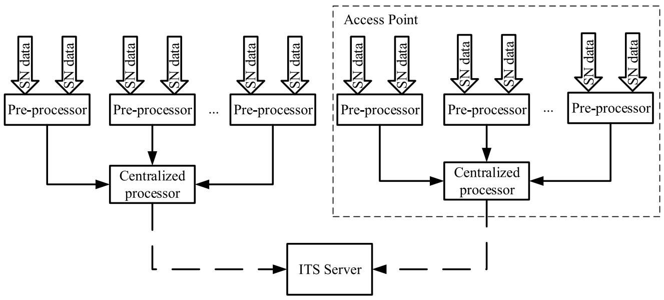
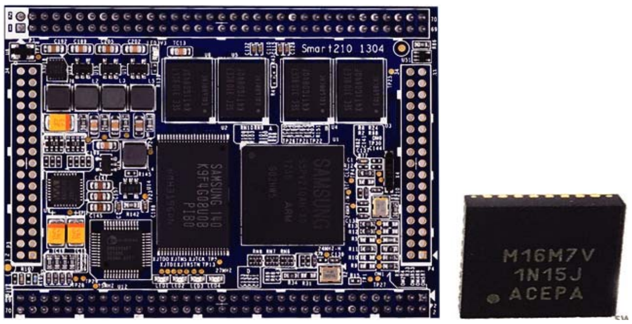


Fig. 3. Architectural design of *SenseMag* with an ITS server.



(a) (b)

Fig. 4. (a) Centralized processor and (b) preprocessor.

B. Design and Implementation of the Centralized Processor, Preprocessors, and the Paired Magnetic Sensors

A centralized processor, as the master node of the system design, controls a set of preprocessors in an access point (AP) [27] shown in Fig. 3. The centralized processor pulls every preprocessor in a round-robin manner and checks whether the preprocessor has any data to upload. Once the pair of magnetic sensors affiliated to the same preprocessor [through analog-to-digital converter (ADC)] detects signal vibrations for possible vehicle passing-by, they cache the signal data in the preprocessor and notifies the centralized processor for data transmission. Indeed, the preprocessor is in charge of providing the sensors reference voltages to control the electric circuit voltage in real time. In addition, the preprocessor also adapts the sampling rate of ADC, so as to obtain the fine-grained time series of magnetic signals while balancing the sensing cost. Note that one preprocessor with its affiliated sensor nodes could well cover an AP, which could refer to one section of the road.

More specifically, with the magnetic signal data transmitted, the centralized processor estimates the speed of vehicle through maximizing the correlation between the signals detected by the two sensors. To avoid the potential affects of noises to the signal processing, *SenseMag* proposes to use Bandstop filter to remove the interference, such as 50 Hz alternating current (ac) frequency. With speed estimated, *SenseMag* first refines the signals using Butterworth low-pass and high-pass filters, then estimates vehicle length though regression. Based on the length of the vehicle, the centralized processor categorizes vehicles into four types. Furthermore, the centralized processor extracts features in the time–frequency domain

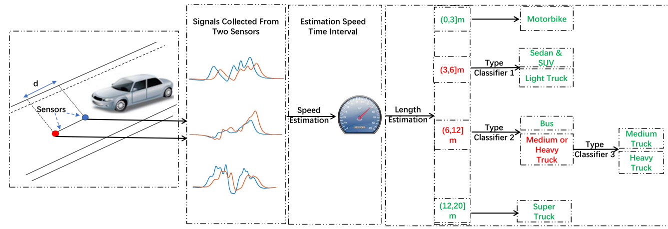
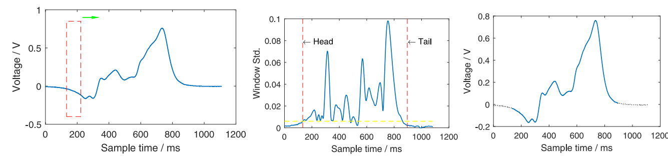


Fig. 5. Hierarchical recognition model for vehicle-type classification.



(a) (b) (c)

Fig. 6. Waveform extraction using standard deviation and sliding window. (a) Original signal. (b) Standard deviation. (c) Extracted waveform.

from the signal and classifies those signal into seven types by using automated machine learning. The final results, including location, time, vehicle number, speed, length, types, etc., packaged by centralized processor, are sent to ITS server.

In our system design here, as shown in Fig. 4(a) and (b), the implementation of the centralized processor is based on an Samsung S5PV210 single board computer with an ARM-11 CortexTM-A8 CPU (clock speed 1 GHz), a main memory of 512-MB DDR2 RAM (200 MHz), and a solid-state drive (SSD) disk for data storage. For every preprocessor, in this work, *SenseMag* adopts a lightweighted ARM Cortex M0+ 32-bit microcontroller unit (MCU) with a clock speed 48 Hz, program storage 128 kB, and data storage 16 kB, due to its low cost and low energy consumption. The resolution of ADC is 16 bit, which provides fine-grained magnetic signal readings over time. All these settings are adjustable to the realistic deployment of the systems.

IV. *SenseMag* CORE ALGORITHMS AND ANALYSIS

Here, we present design of the key *SenseMag* algorithms. With the raw signal received, *SenseMag* adopts a hierarchical recognition model demonstrated in Fig. 5, where the proposed algorithms first predict the speed of vehicle, then identify the length of the vehicle with respect to the speed and the distance between sensor nodes, finally, *SenseMag* classifies the vehicle type using the estimated length and signal features.

A. Vehicle Speed Estimation Models

Given the magnetic signals collected from two sensors, this algorithm estimates the speed of vehicle for the further estimation of vehicle lengths and type classification. The algorithm consists of three steps.

1) *Arrival/Departure Detection:* To estimate the speed, we first need to detect the vehicle that arrives and departs from a sensor node deployed on the road surface. With the raw ADC outputs, *SenseMag* uses a sliding window to filter the time series of ADC outputs, and estimates

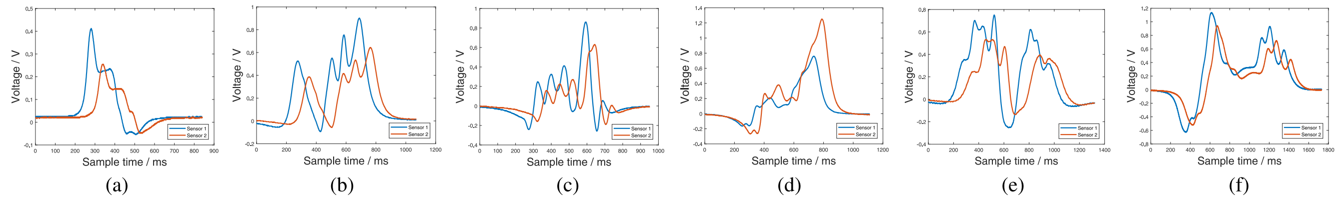


Fig. 7. Examples of magnetic signals collected using two sensors. (a) Sedan and SUV. (b) Light truck. (c) Bus. (d) Medium truck. (e) Heavy truck. (f) Super truck.

the real-time standard deviation of ADC outputs in the sliding window. When the standard deviation in a time point is higher than the predefined threshold, *SenseMag* identifies a significant change of signal in the time point and detects arrivals/departures of the vehicles to/from a sensor node.

2) *Waveform Extraction:* Given the ADC outputs collected from one sensor node and the arrival/departure events detected, *SenseMag* segments the ADC outputs by the events detected and extracts the magnetic signal change caused by the vehicles passing-by. Eventually, when a vehicle passes by, the magnetic sensor readings, as the ADC outputs, would achieve high levels and *SenseMag* picks up the corresponding segments of ADC waveform as the signal caused by the vehicle passing-by. An example of waveform extraction could be found in Fig. 6.

3) *Waveforms Matching:* Given waveforms extracted from two paired sensors, *SenseMag* estimates the speed of vehicle through matching the two waveforms. Fig. 7 illustrates the example of magnetic signals collected from two sensor nodes deployed in the same road section, where we can observe a clear time shift as the vehicle passes the two sensor nodes sequentially with a time gap. Furthermore, as the two waveforms are both caused by the same passing vehicle, they should share a similar pattern in the time domain. One could detect the speed/velocity of the vehicle (denoted as v) by calculating the time shift $\hat{\tau}$ of two waveforms. We define the sampling frequency of ADC is f Hz and the distance between two sensors is d meter. Specifically, we estimate the velocity v km/h as follows:

$$v = 3.6\frac{d \cdot f}{\hat{\tau}} \text{ km/h} \tag{1}$$

where the time shift $\hat{\tau}$ is estimated by maximizing the correlation between the time-shifted waveforms

$$\hat{\tau} = \underset{\tau \in (0,200)}{\operatorname{argmax}} \operatorname{coef}(\tau), \text{ where}$$

$$\operatorname{coef}(\tau) = \frac{\sum_{i=1}^{n}\left(\boldsymbol{x}'_i - \bar{x'}\right)\left(\boldsymbol{x}''_{i+\tau} - \bar{x''}\right)}{n\sqrt{\sum_{i=1}^{n}\left(\boldsymbol{x}'_i - \bar{x'}\right)^2}\sqrt{\sum_{i=1}^{n}\left(\boldsymbol{x}''_i - \bar{x''}\right)^2}}. \tag{2}$$

Note that n refers to the sample points in the waveforms, $\boldsymbol{x}'$ and $\boldsymbol{x}''$ refer to the two waveforms (represented as two n-dimensional vectors), respectively, $\bar{x'}$ is the mean in $\boldsymbol{x}'$, $\bar{x''}$ is the mean in $\boldsymbol{x}''$, $\tau \in (0, 200)$ refers to the potential time shift as the velocity $v \in (0, 200)$ km/h, $d = 1$ m, and $f = 1000$ Hz in our experiment.

Algorithm 1 Semiautomated Learning

Input: Datasets of the signal waveforms $\boldsymbol{X}'$; Minimum velocity of a vehicle is v_{min}; Estimated Speed v;
Output: Lowpass/Highpass Filters $\boldsymbol{F_l}$ and $\boldsymbol{F_h}$; Proportion of Fade-in/Fade-out Periods c in the signal.

```
X^norm ← ∅ /*Initialization*/
for ∀x' ∈ X' do
    x^norm ← interpolate(x')  /*Using Eq. 3*/
    X^norm ← X^norm ∪ {x^norm} /*Adding to X^norm*/
end for
repeat
    Search the parameters for filters F_l and F_h
    Search the proportion of fade-in/fade-out periods c
    Error ← 0
    for ∀x^norm ∈ X^norm do
        x^lh ← F_l(F_h(x^norm)) /*Bandpass Filtering */
        L ← LengthEstimator(x^lh, c) /*Using Eq. 4*/
        if L ∉ range of length by the type then Error++
        end if
    end for
until find the minimum Error.
return Length types.
```

B. Vehicle Length Estimation Models

Given the estimated speed and the two waveforms, *SenseMag* predict the length of vehicle through classifying the length of vehicle. Specifically, we categorize the length in four sets $(0, 3]$, $(3, 6]$, $(6, 12]$ and $(12, 20]$ m, which corresponds to the standard ranges of vehicle lengths proposed by the TPRI [21], Ministry of Transport, China.

Offline Training: To achieve the goal, *SenseMag* adopts automated learning techniques to train the classifier for the prediction. Specifically, there consists of two steps as follows.

1) *Data Collection:* Given waveform extracted from both sensor nodes, we first try to build up a training data set for vehicle length estimation with a given set of vehicles as examples. As what would be disclosed in Section V, we totally include 1000 vehicles in the data collection, where examples of Motorbike (15), Sedan and SUV (350), Light Truck (280), Medium Truck (120), Heavy Truck (85), Super Truck (50), and Bus (100) are included. With the waveforms collected for these 1000 vehicles from the real-world deployments of sensor nodes in xxx road sections, we label every piece of waveform with their corresponding vehicle types and vehicle length.

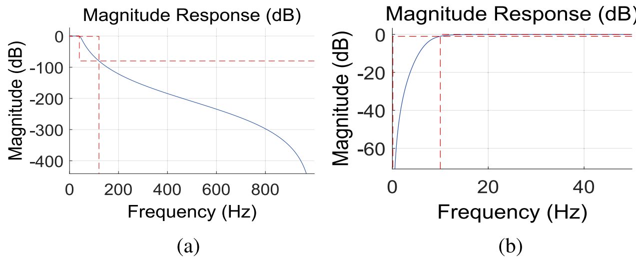


Fig. 8. Butterworth (a) low-pass and (b) high-pass filters. Filters cut the low and high energy of the vehicle waveform. The remaining frequency bands are relatively stable in energy.

2) *Semiautomated Learning:* Given collected data sets $\boldsymbol{X}'$, the goal of this step is to optimize the parameters of a bandpass filter that processes original magnetic signal data from the frequency domain and extracts discriminative features for vehicle length/type classification (see examples in Fig. 2). More specifically, we propose using the semiautomated feature extraction algorithm listed in Algorithm 1 to search the parameters for the filters. First, given every sample in the signal data set $\boldsymbol{x}' \in \boldsymbol{X}'$, *SenseMag* interpolates/normalizes the signal and obtains $\boldsymbol{x}^{\text{norm}}$ using the moving smoother as follows:

$$\boldsymbol{x_i}^{\text{norm}} = \left(1 - \frac{v_{min}}{v}\right)\boldsymbol{x}_i' + \frac{v_{min}}{v}\boldsymbol{x}_{\boldsymbol{i+1}}' \tag{3}$$

where $\boldsymbol{x}_i^{\text{norm}}$ refers to the ith point in the discrete-time signal (n points in total supposed), d refers to the distance between two sensor nodes, and v_{min} refers to the minimal velocity of vehicles. Given the interpolated and normalized data sets $\boldsymbol{X}^{\text{norm}}$, *SenseMag* uses a pair of butterworth low-pass/high-pass filters (See examples in Fig. 8), denoted as $\boldsymbol{F_l}$ and $\boldsymbol{F_h}$, respectively, for bandpass filtering. The algorithm tunes the parameters of the filters. The objective of parameter search is to minimize the training error of length classification using the filtered data $\boldsymbol{x^{lh}} = \boldsymbol{F_l}(\boldsymbol{F_h}(\boldsymbol{x}^{\text{norm}}))$ for $\forall \boldsymbol{x}^{\text{norm}} \in \boldsymbol{X}^{\text{norm}}$. Specifically, *SenseMag* estimates the length of vehicle L (in meters) as follows:

$$L = \frac{d \cdot \text{Cyc}\left(\boldsymbol{x^{lh}}, c\right)}{\hat{\tau} \cdot v} = \frac{\text{Cyc}\left(\boldsymbol{x^{lh}}, c\right)}{3.6 \cdot f} \tag{4}$$

where f refers to the sampling frequency of ADC. $\text{Cyc}(\boldsymbol{x^{lh}}, c)$ counts the effective number of ADC sensing cycles in the filtered signal $\boldsymbol{x^{lh}}$ under the tuning parameter c, which refers to the time spent by the vehicle to pass by the sensor mode. To count the number of effective ADC sensing cycles, *SenseMag* estimates the area under curve of $\boldsymbol{x^{lh}}$ (i.e., total energy) in the temporal domain and removes the fade-in and fade-out periods in the signal, where the fade-in and fade-out periods are supposed to take c proportion (e.g., several percentage) of the area under curve (total energy). Note that the choice of c is also a part of parameter search and the optimal setting searched in our study is $c = 4\%$.

TABLE III
FEATURES EXTRACTED FROM VEHICLE SIGNAL

Features	Meaning
L	vehicle length, equation (4)
$\bar{x_t}$	Average signal strength in time domain
σ_t	MSE in time domain
c_t	Center of gravity in time domain, equation (5)
d_t	Dispersion in time domain, equation (6)
$\bar{x}_f$	Average amplitude in frequency domain
σ_f	MSE in frequency domain
c_f	Center of gravity in frequency domain, equation (8)
d_f	Dispersion in frequency domain, equation (9)

Online Prediction: Given a new sample of the signal obtained in an online setting, *SenseMag* first uses low-pass/high-pass filters to process the signal, then uses the estimator in (4) for length estimation, and categorizes the length in four sets $(0, 3]$, $(3, 6]$, $(6, 12]$, and $(12, 20]$ m. Finally, *SenseMag* forwards the results of length estimation and the processed signal for the further vehicle-type classification.

C. Vehicle-Type Classification Models

Given the estimated vehicle length, the sample of interpolated and normalized signal $\boldsymbol{x}^{\text{norm}}$, *SenseMag* employs a hierarchical classification models (See also in Fig. 5) to identify the types of vehicle in fine-grained, i.e., from four categories of vehicle length to seven types of vehicles. Specifically, *SenseMag* extracts additional eight features from $\boldsymbol{x}^{\text{norm}}$ to train three classifiers to make binary classification: 1) between Sedan versus Light Truck; 2) between Bus versus Median Truck or Heavy Truck; and 3) between Median Truck versus Heavy Truck, respectively.

The extracted features are defined in Table III. The features in temporal domains are calculated as follows:

$$c_t = \frac{\sum_{i=1}^{n} i \cdot \left|\boldsymbol{x}_i^{\text{norm}}\right|}{\sum_{i=1}^{n}\left|\boldsymbol{x}_i^{\text{norm}}\right|} \tag{5}$$

$$d_t = \frac{\sum_{i=1}^{n}(i - c_t)^2 \cdot \left|\boldsymbol{x}_i^{\text{norm}}\right|}{\sum_{i=1}^{n}\left|\boldsymbol{x}_i^{\text{norm}}\right|}. \tag{6}$$

Then, *SenseMag* carries out fast fourier transformation (FFT) to obtain the spectral information as follows:

$$\begin{aligned} \boldsymbol{s} &= \text{FFT}\left(\boldsymbol{x}^{\text{norm}}\right) \\ \boldsymbol{s}_i^{\text{norm}} &= \boldsymbol{s}_i \cdot \frac{f}{n} \quad \forall i \in [1, n] \\ \boldsymbol{s}_i^{\text{low}} &= \boldsymbol{s}_i^{\text{norm}} \quad \forall i \in [1{:}20]. \end{aligned} \tag{7}$$

Note that the interpolation and normalization make the frequency resolution as 1 Hz, and we only consider the spectral data below 20 Hz as the low-band spectral features.

With the spectral information, *SenseMag* forms the features in frequency domains as follows:

$$c_f = \frac{\sum_{i=1}^{n} i \cdot \left|\boldsymbol{s}_i^{\text{low}}\right|}{\sum_{i=1}^{n}\left|\boldsymbol{s}_i^{\text{low}}\right|} \tag{8}$$

$$d_f = \frac{\sum_{i=1}^{n}\left(i - c_f\right)^2 \cdot \left|\boldsymbol{s}_i^{\text{low}}\right|}{\sum_{i=1}^{n}\left|\boldsymbol{s}_i^{\text{low}}\right|}. \tag{9}$$

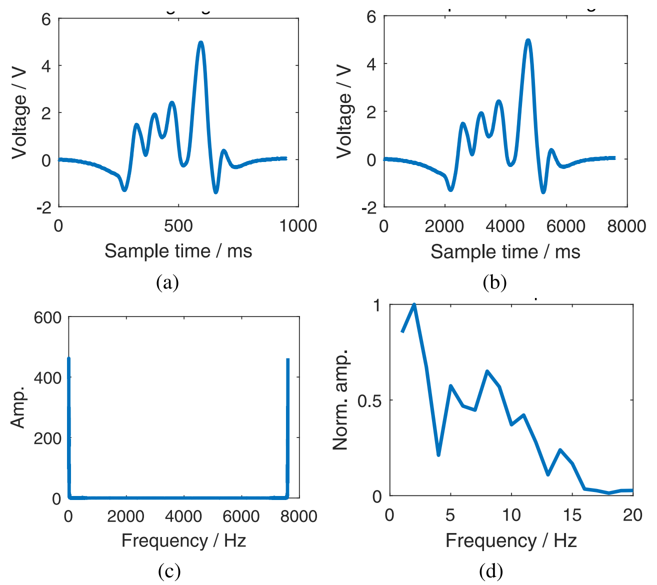


Fig. 9. Examples of (a) original signals, (b) interpolated signals with refined resolution, (c) full spectrum by FFT, and (d) low-band spectrum.

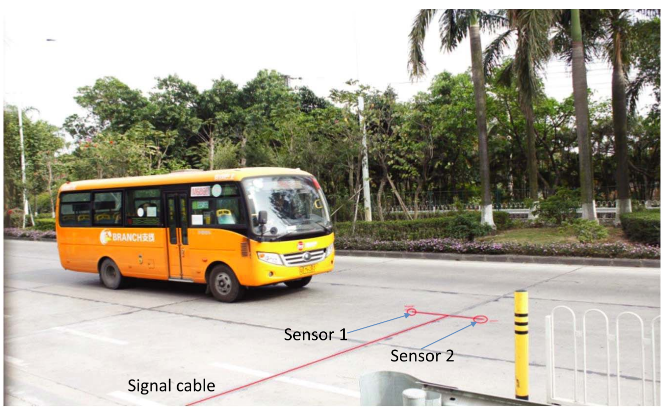


Fig. 10. Examples of real-world deployment: two magnetic sensors were deployed in the road; the distance between the two sensors is 1 m; and the collected data were sent to preprocessors and centralized processor by cables.

An example of the original signals, interpolated signals, full spectral data by FFT, and the low band spectrum is given in Fig. 9. The low-band spectrum well characterizes the vibration of magnetic signals caused by the approaching heavy vehicles. After all, we use all these features to learn the three classifiers using the collected data sets and SVM with Radical Basis Function Kernels (RBF-Kernel SVM) [53], where the nine original features are used.

V. Experiments

In this section, we verify the performance of the proposed method with the real-world deployment. Specifically, we first present the experimental settings and then demonstrate the experimental results and further analysis.

A. Experimental Settings

The data, including seven types of vehicles, utilized in the experiments were collected from the roads in Shenzhen, China

TABLE IV
Confusion Matrix of Vehicle Length Classification

Truth \ Predicted	$(0,3]m$	$(3,6]m$	$(6,12]m$	$(12,20]m$
$(0,3]m$	**15**	0	0	0
$(3,6]m$	0	**806**	35	0
$(6,12]m$	0	16	**255**	2
$(12,20]m$	0	0	1	**23**

(see Fig. 10). In order to prevent overfitting, we randomly select 1000 data pairs for model training, and the rest 1153 data pairs for model performance testing. The details of the testing set are listed in Table IV, in which the lengths of 15 vehicles are $L \in (0, 3]$ m, 841 vehicles are $L \in (3, 6]$ m, 273 vehicles are $L \in (6, 12]$ m, and 24 vehicles are $L \in (12, 20]$ m.

To collect data for training and testing, we use a set of commonly used filters to process signal data. Chebyshev type I bandstop filter is designed using FDESIGN.BANDSTOP. The sampling frequency is $f = 1000$ Hz, order is 2, first passband frequency is 25 Hz, second passband frequency is 100 Hz, and passband ripple is 1 dB. Butterworth high-pass filter is designed using FDESIGN.HIGHPASS. High-pass filter sample frequency is 2000 Hz, stopband frequency is 0.1 Hz, passband frequency is 10 Hz, stopband attenuation is 80 dB, and passband ripple 1 dB. Butterworth low-pass filter is designed using FDESIGN.LOWPASS. Low-pass filter sampling frequency is 2000 Hz, passband frequency is 40 Hz, stopband frequency 120 Hz, stopband attenuation 80 dB, and passband ripple is 1 dB. With all data collected, all computation was conducted on a laptop with an AMD CPU, 8-GB RAM, and Windows 10 operating system, using MATLAB R2017b.

B. Overall Results and Comparisons

With data collected, we carried out the experiments using the proposed algorithms and compare results in three folders.

Vehicle Length Classification: As was discussed, *SenseMag* classifies the type of vehicles according to their lengths and other signal features. In this part, we first intend to understand the accuracy of length classification. Table IV presents the confusion matrix for vehicle length classification. It is obvious that *SenseMag* achieves high accuracy in vehicle length classification, as only 54 samples in all 1153 test cases were misclassified ($\approx 4.7\%$). The major difficulty of vehicle length classification lays on the discriminant between the vehicles in the range of $(3, 6]$ and $(6, 12]$ m. As mentioned, a semi-automated learning paradigm has been used to search the best parameters for high-pass/low-pass filtering and the length estimator. It should be noted that the discriminability of vehicle types between "Sedan and SUV," "Light Truck," "Bus," "Medium Truck," and "Heavy Truck" using *SenseMag* would be bounded by the vehicle length classification.

Vehicle-Type Classification: With vehicle length classified, *SenseMag* enables the vehicle type classification using a hierarchical recognition model. Table V presents the confusion matrix of vehicle-type classification using *SenseMag*. It is obvious that *SenseMag* achieves decent accuracy in vehicle type classification, around 10% testing samples have been misclassified. The misclassification majorly happens between

TABLE V
CONFUSION MATRIX OF VEHICLE TYPE CLASSIFICATION USING *SenseMag*

Truth \ Predicted	Motorbike	Sedan and SUV	Light Truck	Bus	Medium Truck	Heavy Truck	Super Truck
Motorbike	**15**	0	0	0	0	0	0
Sedan and SUV	0	**499**	12	12	8	1	0
Light Truck	0	8	**287**	5	3	6	0
Bus	0	2	2	**66**	3	3	0
Medium Truck	0	2	5	9	**125**	19	1
Heavy Truck	0	0	5	2	2	**26**	1
Super Truck	0	0	0	0	0	1	**23**

TABLE VI
OVERALL COMPARISON RESULTS. N/A: DETAILS WERE NOT DISCLOSED IN THIS ARTICLE

Solutions	Train/Test Data	Features	Classifiers	Precision%/Recall% per Type	Overall Accuracy (%)
Xu *et al.*[17]	140 / 37	Hill-Pattern, Peak-Peak, Mean-Std, and Energy all in Temporal Domain	KNN, RBF-Kernel SVM, and Neural Networks	Two-box (N/A), Saloon (N/A), Bus (N/A), and MPV (N/A)	83.6
SMOTE [18]	130 / 44	3D Magnetic Signals, and FFT	KNN, RBF-Kernel SVM, and Neural Networks	Hatchback (80.0/100.0), Sedan (100.0/92.3), Bus (100.0/100.0), and MPV (75.0/100.0)	95.5
MagMonitor [19]	N/A / N/A	Image, and Histogram of Oriented Gradients (HOG)	RBF-Kernel SVM	Sedan (93.1/95.0), SUV and Van (85.0/79.0), Bus (93.2/96.0), and Truck (89.2/91.0)	87.0
SenseMag	1000 / 1153	9 Features listed in Table III	RBF-Kernel SVM	Motorbike (100.0/100.0), Sedan and SUV (97.7/93.8), Light Truck (92.3/92.3), Bus (70.2/86.8), Medium Truck (88.7/77.6), Heavy Truck (46.4/72.2), and Super Truck (92.0/95.8)	90.3

"Sedan and SUV," "Light Truck," "Bus," "Medium Truck," and "Heavy Truck," partially due to the indiscriminability of signals in vehicle length estimation. In addition to the classification error caused by length estimation, it is often difficult to classify the types of vehicles in the same range of length. For example, 20 of 806 testing samples were misclassified between "Sedan and SUV" and "Light Truck" (both of them are in $(3, 6]$ m length), while, in the categories of "Bus," "Medium Truck," and "Heavy Truck," 38 testing samples were misclassified. In this way, we could conclude that due to the misclassification of vehicle lengths, there were 54 out of 1153 vehicles in the testing enviornment were misclassified (the first layer of the hierarchical model in Fig. 5); due to the misclassification based on the frequency and temporal features of extracted signals, there were 58 vehicles were misclassified (the second layer of the hierarchical model in Fig. 5). In an overall manner, there are totally 112 testing samples were misclassified and the overall accuracy is 90.3%.

Comparisons to Existing Systems: To the proposed system, we compare *SenseMag* with some recent magnetic-based sensing systems for vehicle monitoring, including Xu *et al.* [17] (published in 2017), SMOTE [18] (published in 2018), and MagMonitor [19] (published in 2020). Table VI presents the details in comparisons, including the number of training and testing samples, features, and classifiers used, accuracy details per vehicle type, and the overall classification accuracy. To understand the classification accuracy for every type of vehicle, we calculate the precision and recall for classifying every type of vehicle. Though the overall accuracy of *SenseMag* is slightly lower than the accuracy reported by SMOTE [18], the proposed system can classify vehicles into more fine-grained types. In this way, while these solutions sort vehicles into different categories, we could conclude that: 1) *SenseMag* enables vehicle type classification in an even finer granularity (seven types) compared to other solutions and 2) *SenseMag* achieves comparable classification accuracy in all the seven types.

C. Ablation Studies and Analysis

To further understand *SenseMag*, we carried out extensive ablation studies to evaluate the effectiveness of features and classifiers for the vehicle-type classification.

Using Temporal-Domain Features Only: In this ablation study, we evaluate the accuracy of vehicle type classification using SVM with temporal-domain features only. In general, we follow the hierarchical recognition model shown in Fig. 5 to obtain the vehicle length classification results. With the vehicle length predicted, we use the temporal-domain features listed in Table III to classify the vehicle types. In this way, the classification results for "Motorbike" and "Super Truck" would

TABLE VII
CONFUSION MATRIX OF VEHICLE-TYPE CLASSIFICATION USING TEMPORAL-DOMAIN FEATURES

Truth \ Predicted	Motorbike	Sedan and SUV	Light Truck	Bus	Medium Truck	Heavy Truck	Super Truck
Motorbike	**15**	0	0	0	0	0	0
Sedan and SUV	0	**506**	5	5	7	9	0
Light Truck	0	233	**62**	5	0	9	0
Bus	0	4	0	**8**	60	4	0
Medium Truck	0	2	5	25	**31**	97	1
Heavy Truck	0	1	4	1	1	**28**	1
Super Truck	0	0	0	0	0	1	**23**

TABLE VIII
CONFUSION MATRIX OF VEHICLE-TYPE CLASSIFICATION USING FREQUENCY-DOMAIN FEATURES

Truth \ Predicted	Motorbike	Sedan and SUV	Light Truck	Bus	Medium Truck	Heavy Truck	Super Truck
Motorbike	**15**	0	0	0	0	0	0
Sedan and SUV	0	**506**	5	15	2	4	0
Light Truck	0	224	**71**	9	1	4	0
Bus	0	2	2	**29**	3	13	0
Medium Truck	0	1	6	90	**61**	2	1
Heavy Truck	0	1	4	2	1	**27**	1
Super Truck	0	0	0	0	0	1	**23**

not be changed. The confusion matrix of vehicle-type classification using temporal-domain features is listed in Table VII. It is obvious that the solution based on temporal-domain features only suffers the serious performance degradation. Specifically, the algorithm in this setting proportionally misclassifies: "Light Truck" into the type of "Sedan and SUV," "Medium Truck" into the type of "Bus," and "Bus" into the type of "Medium Truck."

Using Frequency-Domain Features Only: In this ablation study, we evaluate the accuracy of vehicle-type classification using SVM with frequency-domain features only. We also follow the hierarchical recognition model shown in Fig. 5 and replace the three classifiers in the second layer with the ones based on the frequency-domain features (listed in Table III). The confusion matrix of vehicle-type classification using temporal-domain features is listed in Table VIII. It is obvious that the solution based on frequency-domain features only suffers the serious performance degradation. Specifically, the algorithm in this setting proportionally misclassifies: "Sedan and SUV" into the types of "Light Truck" and "Bus," "Light Truck" into the type of "Sedan and SUV," "Bus" into the type of the type of "Medium Truck," and "Medium Truck" into the type of "Heavy Truck."

Using Other Classifiers: In our work, we select RBF-Kernel SVM as the classifiers through a simple automated learning procedure via the comparisons of cross-validation accuracy. To understand the superiority of RBF-Kernel SVM in *SenseMag* tasks, we replace RBF-Kernel SVM learners used in *SenseMag* with other classifiers, including the Random Forest, Adaboost, Neural Network, and so on. In all settings, we find significant performance degradation in terms of overall classification accuracy. The second-best learner for our task is the Random Forest Classifier. Table IX demonstrates the confusion matrix of vehicle-type classification using Random Forest Classifiers with both temporal-domain and frequency-domain features. Compared to *SenseMag*, a Random Forest Classifier might cause more errors in classifying vehicular types between "Sedan and SUV" and "Light Truck," "Bus" and "Medium Truck," and "Medium Truck" and "Heavy Truck" obviously.

We believe RBF-Kernel SVM outperforms other algorithms due to two reasons as follows: 1) RBF-Kernel SVM leverages kernel tricks to project the data in the original feature space into a high-dimensional nonlinear kernel space, where the samples are more discriminative and distinguishable and 2) the SVM classifier adopts a max-margin loss that aims at minimizing the confusion between the overlapped types (e.g., "Medium Truck" and "Heavy Truck") [54].

D. Time Consumption Analysis

We analyze the runtime records of all 1153 vehicles in the experiment and estimate the end-to-end time consumption (from detecting a passing vehicle to classifying its type) for every vehicle. For all type of vehicles, the average time consumption of *SenseMag* for recognize one vehicle is 0.0995 ± 0.0183 s. We believe the average measure of time consumption is reliable, as the variance-to-mean ratio (VMR) is $0.018^2/0.0995 = 0.32\%$ close to 0 (i.e., small dispersion against a stable mean).

To provide an estimate of worst case execution time (WCET) [55], we calculate the confidence upper bound of the time consumption using the Six-Sigma standard for extreme value estimates [56], which should be $0.0995 + 6.0 \times 0.0183 = 0.2093$ s in our experiments. Note that in the normal traffic condition of a highway, vehicles on every lane should pass by the sensor nodes sequentially in a one-by-one manner. Moreover, in the practice, it frequently recommends a minimum time gap of 2.0 between two consecutive vehicles for driving safety [57]. In this way, we could conclude that the time consumption of *SenseMag* indeed ensures the real-time performance of traffic monitoring.

TABLE IX
CONFUSION MATRIX OF VEHICLE-TYPE CLASSIFICATION USING BOTH TIME-DOMAIN AND FREQUENCY-DOMAIN FEATURES AND RANDOM FOREST CLASSIFIERS

Truth \ Predicted	Motorbike	Sedan and SUV	Light Truck	Bus	Medium Truck	Heavy Truck	Super Truck
Motorbike	**15**	0	0	0	0	0	0
Sedan and SUV	0	**462**	49	10	9	2	0
Light Truck	0	75	**220**	8	0	6	0
Bus	0	1	3	**43**	27	2	0
Medium Truck	0	7	0	1	**92**	60	1
Heavy Truck	0	3	2	1	2	**27**	1
Super Truck	0	0	0	0	0	1	**23**

VI. Discussion and Limitations

There are several limitations in our study. Here, We discuss some of the limitations and technical issues as follows.

A. Hierarchical Recognition Models

Instead of proposing an end-to-end model for classifying the vehicle types from raw signals, *SenseMag* recognizes the vehicle types in three steps: 1) speed/velocity estimation; 2) vehicle length estimation/classification (in four categories); and 3) vehicle-type classification (in seven categories). The proposed algorithm push the granularity of vehicle type classification finer and finer. In our experiments, totally 112 out of 1153 (9.7%) testing samples were misclassified. While 48.2% (54 out of 112) errors were due to the misclassification of vehicle length, the rest 51.8% was caused by the vehicle type classification using temporal/frequency-domain features. It is reasonable to assume the use of some end-to-end approach based on raw signal features could outperform the proposed solutions. However, compared to the existing work [17]–[19], the overall accuracy of *SenseMag* tops while the types/categorization of vehicles are finest.

Note that we consider the estimated speeds and lengths of vehicles as two key features for the hierarchical recognition framework due to two reasons as follows: 1) the types of vehicles are majorly categorized by the lengths of vehicles according to the standard recommended by transportation administration and authorities [21] and 2) it frequently needs to first measure the speed of a vehicle and further estimate its length using the measured speed and the measured time duration for the vehicle to drive through the two sensor nodes. Ofcourse, other features, including heights and weights of vehicles might also help for classification. We consider the proposed *SenseMag* as an alternative solution of the problem, which could complement with other existing tools and systems for better overall performance.

B. Validation of Speed/Velocity Estimation

The vehicle length and type classification of *SenseMag* majorly relies on the estimation of vehicle speed/velocity. In our research, we collect vehicle data under the real-world deployment of the *SenseMag* system using magnetic sensors on the road surface and video recorders surveilling the road section. We recruit professional labellers to recognize the models of vehicles, and label the collected signals with the vehicle types and lengths. In this way, we did not collect the real-time speed/velocity of vehicles as the label of data and, thus, cannot evaluate the accuracy of speed/velocity estimation. All in all, *SenseMag* infers the length of vehicle using the estimated speed through a white-box physical model [in (4)]. As the overall vehicle length/type classification is accurate, we can conclude that the speed/velocity estimation of *SenseMag* did not cause significant performance degradation for the further steps.

C. Shallow Models and Deep Learning

SenseMag employs an semiautomated procedure to extract temporal/frequency-domain features from raw magnetic signals and adopts statistical models/learners are used to handle the classification tasks. Because the features used in *SenseMag* are with relatively low dimensions, it is no doubt that the use of some deep neural networks could achieve better performance when stacking feature learning and discriminative learning in an end-to-end optimization manner. The contribution of our study is to demonstrate the feasibility of using a hierarchical recognition model that infer the type of vehicles step-by-step from speed estimation, to length estimation, and finally, to the vehicle-type classification, in an interpretable way.

D. Sensor and Vehicle Coordination

To estimate speed, *SenseMag* assumes that the vehicles would go straight through the two magnetic sensors, and the speed/velocity of the vehicle should be in a certain range with respect to the sampling rate of ADC and the distance between sensors. In fact, *SenseMag* deploys sensors on the straight section of highways and the distance between two sensor nodes is $d = 1$ m in our experiments. In this way, we are pretty sure that the vehicles should pass the two sensors in a straight line. As the sampling frequency is set to $f = 1000$ Hz , *SenseMag* can well detect the vehicles going through the sensor nodes with a velocity in the range of $(20,\ 150]$ km/h. Moreover, the performance of *SenseMag* could be improved using the VoV and VoI communications [47].

E. Weathers, Noises, and Other Factors May Affect the Performance

Some environmental factors, including extreme weather conditions, electromagnetic interference, vibration of road surfaces, and ac harmonics, would affect the working conditions of magnetic sensors and *SenseMag*. For the noises caused by harmonics in ac power, vibration of road surfaces, and electromagnetic interference, *SenseMag* tries to eliminate the effects of noises to classification results through filtering. Specifically, *SenseMag* adopts a well-designed bandstop filter to remove the effects of harmonics and the power frequency (e.g., 50 Hz in China and Europe) in ac. Then, a pair of high-pass and low-pass filters has used to remove the effects of electromagnetic interference in some bands. Furthermore, *SenseMag* considers the vibration of road surfaces (especially when heavy vehicles are approaching or departing) and tries to remove the effects of road surface vibration through filtering the temporal signals in the "fade-in" and "fade-out" periods. Note that the parameters for high-pass/low-pass filters and fade-in/fade-out periods detection are all fine-tuned with automated learning techniques with appropriate validations. Finally, to handle extreme weather conditions, it is highly recommended to complement *SenseMag* with other traffic monitoring tools (e.g., vision-based or radar-based solutions) to achieve good performance in general.

VII. Conclusion

The operation and management of ITS relies on the real-time recognition of vehicle types (e.g., cars, trucks, and buses), in the critical roads and highways. In our research, we proposed *SenseMag*, which recognizes the types of running vehicles using a pair of magnetic sensor nodes deployed on the surface of road section. Specifically, *SenseMag* filters out noises and segments received magnetic signals by the time points that the vehicle arrives or departs from every sensor node. Furthermore, *SenseMag* adopts a hierarchical recognition model to first estimate the speed/velocity and later identify the length of vehicle using the predicted speed and the distance between the sensor nodes. With the vehicle length identified and the temporal/spectral features extracted from the magnetic signals, *SenseMag* classify the types of vehicles accordingly. More specifically, *SenseMag* adopts semiautomated learning techniques to optimize the parameters of low-pass/high-pass filters, design of features, and the choice of hyperparameters for length estimation. Extensive experiment based on real-word field deployment (on the highways in Shenzhen, China) showed that *SenseMag* significantly outperforms the existing methods in both classification accuracy and the granularity of vehicle types (i.e., seven types by *SenseMag* versus four types by the existing work [17]–[19]). To be specific, our field experiment results validated that *SenseMag* is with at least 90% vehicle-type classification accuracy and less than 5% vehicle length classification error.

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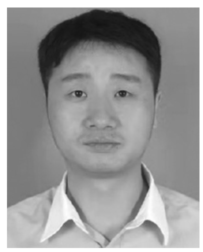

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