SenseMag: Enabling Low-Cost Traffic Monitoring using Non-invasive 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 paper introduces a low-cost method, namely SenseMag, to recognize the vehicular type using a pair of non-invasive 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. Further, SenseMag adopts a hierarchical recognition model to first estimate the speed/velocity, then identify the length of 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 classify the types of vehicles accordingly. Some semi-automated learning techniques have been adopted for the design of filters, features, and the choice of hyper-parameters. 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., 7 types by SenseMag versus 4 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.

Keywords: Magnetic Sensing, Traffic Monitoring, Vehicle Type Classification, Internet of Vehicles (IoV).

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 hour, 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: infrastructure-based approach [3], [4] and infrastructure-less approach [5], [6]. To build an infrastructure for traffic monitoring, 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 infrastructure-less approach, one can obtain the information about vehicular type and speed using vehicular-embedded GPS sensors in a so-called crowdsensing manner [7], [8], [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 onto each road of the city in real-time. Note that GPS-based solution no longer works when the user turns...
TABLE I: Vehicle Types and the Standard Ranges of Vehicle Lengths in China

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

off the mobility tracking, while the deployment of camera networks relies on the huge monetary investment. Further, both existing infrastructure-based and infrastructure-less techniques would invade the privacy of drivers. All above issues would burden the scalability of traffic monitoring. Thus a low cost method is needed to obtain 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 non-invasive manner [12], [13], [14], [15], [16], [17], [18], [19]. Figure 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 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 magnetic field and start to collect magnetic field signals for further processing and recognition.

For example, Figure 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 identified vehicular types and speed, one can use general purpose supervised learning techniques to identify the vehicles and classify the vehicular type. Such 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 through obtaining the time spent by the vehicle for driving through the sensor node from nose to tail.

With the vehicle length estimated, according to Table I, one could categorize vehicles into 4 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, aforementioned solution is with significant limitations as follows: (1) From the raw magnetic signals illustrated in Figure 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; (2) No matter from the temporal or frequency domains (shown in Figure 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, that intends to classify the vehicular type through magnetic sensing, signal processing, and semi-automated 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. Further, SenseMag adopts a hierarchical recognition model to first estimate the speed/velocity, and latter 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.

Compared to the general purpose magnetic approaches, with a collection of labeled signals, SenseMag adopts several semi-automated 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 Figures 2 (c) and (d). In Figure 2 (c), we could clearly observe the time duration that the vehicle drives through the sensor node from the processed signals in temporal domain. Further, Figure 2 (d) shows the discriminability of processed signals in both temporal/frequency domains by the vehicle types. We have made at least following three contributions:

(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 through 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 semi-automated 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 de-noising 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 lowpass/highpass filters as well as the hyperparameters for length estimation through semi-automated 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 — 4 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], [18], [19] in both classification accuracy and the number of recognizable vehicle types (7 types by SenseMag versus 4 types in [17], [18], [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 types classification using magnetic sensors.

A. Related Works

Magnetic sensing has been used in vehicular traffic surveillance [12], [13], [14], [15], including detecting vehicles, estimating speed of vehicles, re-identify vehicle, and classifying the vehicle types. Incorporating Anisotropic Magneto-Resistive (AMR) signals measured from magnetic, [12] propose 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 multi-sensor 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], [25], [26], [27], [28], [29], [30], [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 ans studied in [23], [32], [19], [33], [34], [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], [37], [38], [39], [40], [41], [42], [43], [44], [45], where the wave pattern matching of magnetic signals has been adopted in the algorithms.

More specifically, [45] propose 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 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], [48], [19]. Particularly, [17] proposed a portable roadside magnetic sensors for vehicle type classification, where they tried to classify vehicles into 4 types with the classification accuracy 83.02%. Specifically, they use the Hill-Pattern, Peak-Peak, Mean-Std and Energy as features. Various supervised learners, including K-nearest neighborhood (KNN), Support vector machine (SVM) and back-propagation neural network (BPNN) have been used for classification. Velisavljevic’s system [48] could achieve classification accuracy rate of 88.37% with 5 vehicle classes when was evaluated on a large realistic dataset. While all 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 learning [49], [50], [51], [52] that searches the empirically best classifiers with fine-tuned features and hyper-parameters 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 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 existing classification work may be affected by too little realistic data. The proportion of vehicle type in existing work data set is far away to most country roads or urban road. Heuristically, speed and length of vehicle are those of the most important features that the magnetic sensor can detect precisely. Length can be used for classify some vehicles in big classification. Our works is the first use magnetic sensing measure vehicle speed and length for big classification, then use integral features of time-frequency domain get higher vehicle classification. Only use two sensor 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.

### TABLE II: Notations for SenseMag

| Notations | Meaning |
|-----------|---------|
| \(d\) | Two sensors distance |
| \(f\) | ADC frequency of pre-processor |
| \(x'\) | Original signal vector from the first sensor |
| \(x''\) | Original signal vector from the second sensor |
| \(x\) | Bandstop filtered signal vector for \(x'\) |
| \(x_{\text{norm}}\) | Interpolated normalization for original signal vector |
| \(x_{\text{TH}}\) | Lowpass and highpass filtered signal vector for \(x_{\text{norm}}\) |
| \(X\) | Frequency domain signal vector for \(x_{\text{TH}}\) |
| \(X'\) | Normalize frequency domain signal vector \(X\) |
| \(X_{\text{LOW}}\) | Low frequency of truncated vector \(X'\) |
| \(P_s\) | Chebyshev type I bandstop filter |
| \(P_l\) | Butterworth lowpass filter |
| \(P_h\) | Butterworth highpass filter |
| \(\tau\) | Cross-correlation translation |
| \(v\) | Velocity of vehicle |
| \(L_0\) | Real length of vehicle |
| \(L\) | Length of vehicle |
(through Analog-to-Digital Converter, ADC) detects signal vibrations for possible vehicle passing-by, they cache the signal data in the pre-processor and notifies the centralized processor for data transmission. Indeed, the pre-processor is in charge of providing the sensors reference voltages to control the electric circuit voltage in real-time. In addition, the pre-processor 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 pre-processor 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 lowpass and highpass filters, then estimates vehicle length though regression. Based on the length of vehicle, the centralized processor categorizes vehicles into 4 types. Furthermore, the centralized processor extracts features in time-frequency domain from the signal and classifies those signal into 7 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 Figures 4(a) and (b), the implementation of centralized processor is based on an Samsung S5PV210 single board computer with an ARM-11 CortexTM-A8 CPU (clock speed 1GHz), a main memory of 512MB DDR2 RAM (200Mhz), and a solid-state drive (SSD) disk for data storage. For every pre-processor, in this work, SenseMag adopts a light-weighted ARM Cortex M0+ 32-bit Microcontroller Unit (MCU) with a clock speed 48Hz, program storage 128KB, and data storage 16 KB, due to its low cost and low energy consumption. The resolution of Analog-to-Digital Converter (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.

Fig. 4: Centralized Processor and Pre-processor .

IV. SensMag 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 Figure 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:

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

- **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.
- **Waveforms Matching.** Given waveforms extracted from two paired sensors, SenseMag estimates the speed of the vehicle through matching the two waveforms. Figure 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 $v$) through 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 follow

$$v = 3.6 \frac{d \cdot f}{\bar{\tau}} \text{ km/h} ,$$  

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

$$\hat{\tau} = \arg \max_{\tau \in (0, 200)} \text{coef}(\tau),$$

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

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

**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 $(0, 3)m$, $(3, 6)m$, $(6, 12)m$ and $(12, 20)m$, which corresponds to the standard ranges of vehicle lengths proposed by the Transport Planning and Research Institute (TPRI) [21], Ministry of Transport, China.

**Off-line training.** To achieve the goal, SenseMag adopts automated learning techniques to train the classifier for the prediction. Specifically, there consists of two steps as follow.

- **Data Collection.** Given waveform extracted from both sensor nodes, we first try to build up a training dataset for vehicle length estimation with a given set of vehicles as examples. As what would be disclosed in Section V, we totally include 1,000 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 waveforms collected for these 1,000 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.

- **Semi-Automated Learning.** Given collected datasets $X'$, 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 semi-automated feature extraction algorithm listed in Algorithm 1 to search the parameters for the filters. First of all, given every sample in the signal dataset $x' \in X'$, SenseMag interpolates/normalizes the signal and obtains the $x''_i$ using the moving smoother as follow.

$$x''_i = (1 - \frac{v_{min}}{v}) \cdot x'_i + \frac{v_{min}}{v} \cdot x'_{i+1}$$

where $x''_i$ refers to the $i^{th}$ point in the discrete-

![Fig. 7: Examples of Magnetic Signals Collected using Two sensors](image)

**Algorithm 1 Semi-Automated Learning**

**Input:** Datasets of the signal waveforms $X'$; Minimum velocity of a vehicle is $v_{min}$; Estimated Speed $v$.

**Output:** Lowpass/Highpass Filters $F_l$ and $F_h$; Proportion of Fade-in/Fade-out Periods $c$ in the signal.

1. $X_{\text{norm}} \leftarrow \emptyset$ /*Initialization*/
2. for $\forall x' \in X'$ do
3. $x''_{\text{norm}} \leftarrow \text{interpolate}(x')$ /*Using Eq. 3*/
4. $X_{\text{norm}} \leftarrow X_{\text{norm}} \cup \{x''_{\text{norm}}\}$ /*Adding to $X_{\text{norm}}$*/
5. end for
6. repeat
7. Search the parameters for filters $F_l$ and $F_h$
8. Search the proportion of fade-in/fade-out periods $c$
9. Error $\leftarrow 0$
10. for $\forall x''_{\text{norm}} \in X_{\text{norm}}$ do
11. $x''_{\text{th}} \leftarrow F_l(F_h(x''_{\text{norm}}))$ /*Bandpass Filtering*/
12. $L \leftarrow \text{LengthEstimator}(x''_{\text{th}}, c)$ /*Using Eq. 4*/
13. if $L \notin$ range of length by the type then Error $++$
14. end if
15. end for
16. until find the minimum Error.
17. return Length types.
time signal \((n\) points in total supposed), \(d\) refers to the distance between two sensor nodes, and \(v_{\text{min}}\) refers to the minimal velocity of vehicles. Given the interpolated and normalized datasets \(X^\text{norm}\), \SenseMag\ uses a pair of butterworth lowpass/highpass filters (See examples in Fig. 8), denoted as \(F_l\) and \(F_h\) 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 \(x^{\text{th}} = F_l((F_h(x^{\text{norm}}))) \) for \(\forall x^{\text{norm}} \in X^\text{norm}\). Specifically, \SenseMag\ estimates the length of vehicle \(L\) (in meters) as follow,

\[
L = \frac{d \cdot \text{Cyc}(x^{\text{th}}, c)}{f \cdot v} = \frac{\text{Cyc}(x^{\text{th}}, c)}{3.6 \cdot f}.
\]

where \(f\) refers to the sampling frequency of ADC. \text{Cyc}(x^{\text{th}}, c) counts the effective number of ADC sensing cycles in the filtered signal \(x^{\text{th}}\) 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 \(x^{\text{th}}\) (i.e., total energy) in 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 \(c = 4\%\).

Fig. 8: Butterworth Lowpass and Highpass Filters. Filters cut the low and high energy of vehicle waveform. The remaining frequency bands are relatively stable in energy.

**On-line prediction.** Given a new sample of signal obtained in on-line setting, \SenseMag\ first uses lowpass/highpass filters to process the signal, then uses the estimator in Eq. 4 for length estimation, and categorizes the length in four sets \((0, 3]m, (3, 6]m, (6, 12]m 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 \(x^{\text{norm}}\), \SenseMag\ employs a hierarchical classification models (See also in Figure 5) to identify the types of vehicle in fine-grained, i.e., from 4 categories of vehicle length to 7 types of vehicles. Specifically, \SenseMag\ extracts additional 8 features from \(x^{\text{norm}}\) to train 3 classifiers to make binary classification: (1) between Sedan vs Light Truck, (2) between Bus vs Median Truck or Heavy Truck, and (3) between Median Truck vs Heavy Truck respectively.

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

\[
c_t = \frac{\sum_{i=1}^{n} i \cdot |x^{\text{norm}}|}{\sum_{i=1}^{n} |x^{\text{norm}}|}
\]

\[
d_t = \frac{\sum_{i=1}^{n} (i - c_t)^2 \cdot |x^{\text{norm}}|}{\sum_{i=1}^{n} |x^{\text{norm}}|}
\]

Then \SenseMag\ carries out Fast Fourier Transformation (FFT) to obtain the spectral information as follow.

\[
s = \text{FFT}(x^{\text{norm}})
\]

\[
s_i^{\text{norm}} = \frac{s_i}{n} \quad \forall i \in [1, n]
\]

\[
s_i^{\text{low}} = s_i^{\text{norm}} \quad \forall i \in [1, 20]
\]

Note that the interpolation and normalization makes the frequency resolution as 1Hz, 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 follow.

\[
c_f = \frac{\sum_{i=1}^{n} i \cdot |s_i^{\text{low}}|}{\sum_{i=1}^{n} |s_i^{\text{low}}|}
\]

\[
d_f = \frac{\sum_{i=1}^{n} (i - c_f)^2 \cdot |s_i^{\text{low}}|}{\sum_{i=1}^{n} |s_i^{\text{low}}|}
\]

An example of original signals, interpolated signals, full spectral data by FFT, and the low band spectrum is given in Figure 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 datasets and Support Vector Machine with Radial Basis Function Kernels (RBF-Kernel SVM) [53], where the 9 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 7 types of vehicles, utilized in the experiments were collected from the roads in Shenzhen, China (see Fig. 9). In order to prevent over-fitting, 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, passband ripple is 1 dB. Butterworth highpass filter is designed using FDESIGN.HIGHPASS. Highpass filter sample frequency is 2000 Hz, stopband frequency is 0.1 Hz, stopband attenuation is 80 dB and passband ripple 1 dB. Butterworth lowpass filter is designed using FDESIGN.LOWPASS. Lowpass 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, 8G 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 $(3, 6]m$ and $(6, 12]m$. As was mentioned, a semi-automated learning paradigm has been used to search the best parameters for highpass/lowpass 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 “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 environment were misclassified (the first layer of the hierarchical model in Figure 5); due to the misclassification based on the frequency and temporal features

![Fig. 9: Examples of Original Signals, Interpolated Signals with Refined Resolution, Full Spectrum by FFT, and the Low Band Spectrum.](image)

![Fig. 10: Examples of Real-world Deployment: Two magnetic sensors were deployed in the road; the distance between the two sensors is 1 meter; and the collected data were sent to pre-processors and centralized processor by cables.](image)

| Truth | Predicted |
|-------|-----------|
| (0, 3]m | 15 |
| (3, 6]m | 0, 806, 35 |
| (6, 12]m | 0, 16, 255 |
| (12, 20]m | 0, 0, 1, 23 |

**TABLE IV: Confusion Matrix of Vehicle Length Classification**

![Interpolated Waveform](image)

![Lowband Spectrum](image)
of extracted signals, there were 58 vehicles were misclassified (the second layer of the hierarchical model in Figure 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 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 (7 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 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 support vector machine with Temporal Domain Features only. In general, we follow the hierarchical recognition model shown in Figure 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 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 support vector machine with Frequency Domain Features only. We also follow the hierarchical recognition model shown in Figure 5 and replace the three classifiers in the second layer with 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 degra-
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           | 0           |
| Sedan and SUV| 0               | 506       | 5             | 7          | 9   | 0           | 0           | 0           |
| Light Truck | 0               | 233       | 62            | 5          | 0   | 9           | 0           | 0           |
| Bus         | 0               | 4         | 0             | 8          | 60  | 4           | 0           | 0           |
| Medium Truck| 0               | 2         | 5             | 25         | 31  | 91          | 1           | 1           |
| Heavy Truck | 0               | 1         | 4             | 1          | 1   | 28          | 1           | 1           |
| Super Truck | 0               | 0         | 0             | 0          | 0   | 1           | 23          |             |

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 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 and Frequency Domain Features. Compared to SenseMag, Random Forest Classifier might cause more errors in classifying vehicular types between “Sedan and SUV” and “Light Truck”, “Bus” and “Medium Truck”, “Medium Truck” and “Heavy Truck” obviously.

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 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 and Frequency Domain Features. Compared to SenseMag, Random Forest Classifier might cause more errors in classifying vehicular types between “Sedan and SUV” and “Light Truck”, “Bus” and “Medium Truck”, “Medium Truck” and “Heavy Truck” obviously.

We believe RBF-Kernel SVM outperforms other algorithms due to two reasons as follows. (I) RBF-Kernel SVM leverages kernel tricks to project the data in orginal feature space into a high-dimensional nonlinear kernel space, where the samples are more discriminative and distinguishable; and (II) 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 seconds. We believe the average measure of time consumption is reliable, as the Variance-to-Mean Ratio (VMR) is 0.0182/0.0995 = 0.32% close to zero (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+6.0×0.0183 = 0.2093 seconds 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.

VI. DISCUSSION AND LIMITATIONS

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

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 4 categories), and (3) vehicle type classification (in 7 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 existing work [17], [18], [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. (I) The types of vehicles are majorly categorized by the lengths of vehicles according to the standard recommended by transportation administration and authorities [21]; and (II) 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. Of-course, 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 real-world deployment of 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
TABLE VIII: Confusion Matrix of Vehicle Type Classification using Frequency Domain Features.

| Predicted   | Motorbike | Sedan and SUV | Light Truck | Bus | Medium Truck | Heavy Truck | Super Truck |
|-------------|-----------|---------------|-------------|-----|--------------|-------------|-------------|
| Truth       |           |               |             |     |              |             |             |
| 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          |

TABLE IX: Confusion Matrix of Vehicle Type Classification using both Time and Frequency Domain Features and Random Forest Classifiers.

| Predicted   | Motorbike | Sedan and SUV | Light Truck | Bus | Medium Truck | Heavy Truck | Super Truck |
|-------------|-----------|---------------|-------------|-----|--------------|-------------|-------------|
| Truth       |           |               |             |     |              |             |             |
| Motorbike   | 15        | 0             | 0           | 0   | 0            | 0           | 0           |
| Sedan and SUV| 0        | 462           | 49          | 10  | 9            | 2           | 0           |
| Light Truck | 0         | 75            | 220         | 8   | 6            | 0           | 0           |
| Bus         | 0         | 1             | 5           | 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          |

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 Eq. 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 semi-automated 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) Sensors and Vehicles 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 \(d = 1m\) 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 Vehicle-to-Vehicle (VoV) and Vehicle-to-Infrastructure (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 alternating current (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 highpass and lowpass filters has used to remove the effects of electromagnetic interference in some bands. Further, 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 highpass/lowpass filters and fade-in/fade-out periods detection are all fine-tuned with automatic 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 intelligent transportation systems (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 propose SenseMag, that 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. Further, SenseMag adopts a hierarchical recognition model to first
estimate the speed/velocity, and latter 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 semi-automated learning techniques to optimize the parameters of lowpass/highpass filters, design of features, and the choice of hyper-parameters for length estimation. 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., 7 types by SenseMag versus 4 types by the existing work [17], [18], [19]). 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.

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