This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3120470, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.DOI

A Multivariate Analysis Framework for Vehicle Detection from Loop Data under Heterogeneous and Less Lane Disciplined Traffic

NIRAJ KUMAR SINGH[1], ARUN K. TANGIRALA[2], (Member, IEEE), and LELITHA DEVI VANAJAKSHI[3].

[1]Systems Engineering and Data Sciences Group, Department of Chemical Engineering, Indian Institute of Technology Madras, Chennai-600036, India (e-mail: nks.iitm@gmail.com)
[2]Systems Engineering and Data Sciences Group, Department of Chemical Engineering, Indian Institute of Technology Madras; Faculty, RBCDSAI, IIT Madras, Chennai-600036, India (e-mail: arunkt@iitm.ac.in)
[3]Transportation Engineering Division, Department of Civil Engineering, Indian Institute of Technology Madras; Faculty, RBCDSAI, IIT Madras, Chennai-600036, India (e-mail: lelitha@iitm.ac.in)

Corresponding author: Arun K. Tangirala (ORCID ID: 0000-0002-7921-5340, e-mail: arunkt@iitm.ac.in).

Authors acknowledge the 'Connected Intelligent Urban Transportation Lab', funded by the Ministry of Human Resource Development, Government of India, through project number CEMHRD008432.

ABSTRACT Accurate vehicle detection in real-time is a challenging problem for engineers and researchers working in the field of transportation engineering all over the world. To detect the vehicle presence in the lane-based traffic, one of the widely used traffic detectors is inductive loop detectors (ILD). For less lane disciplined and heterogeneous traffic, researchers have suggested another traffic detector known as a multiple inductive loop detector (MILD) system. In order to extract the vehicle count from MILD data, it is required to detect vehicle presence and segment the signature of different vehicles. This work is focused on the automated processing of MILD signals to get total vehicle count information in real-time under heterogeneous and less-lane disciplined traffic conditions. This study proposes a multivariate data analysis framework for the detection and segmentation of vehicle signature from the acquired data, without significant manual intervention. The major challenge in this process is the coupling of the multi-dimensional loop data, due to cross-talk across the loops. To address this, principal component analysis (PCA) is used with the additional benefit of dimensionality reduction. Though PCA is a well-known method, its application to the current problem is not trivial and calls for tailoring of the method. Here, a new PC selection strategy suitable for data under consideration is proposed, as the traditional approach does not fit this application and tends to be low accuracy. Subsequently, the principal components are processed using a threshold-based method, which uses the mean absolute deviation measure, to detect the vehicle presence. The results show that the developed algorithm with the proposed strategy for PC selection achieved an average vehicle count accuracy of 90.38 % whereas with the traditional approach the accuracy is 24.31 %.

INDEX TERMS Vehicle detection, multiple inductive loop detectors (MILD), PCA, mean absolute deviation, multivariate analysis, intelligent transportation system (ITS).

I. INTRODUCTION

URBAN transportation is a sector that needs significant improvement, as cities are getting revamped all over the world. With limited infrastructure growth and a multi-fold increase in vehicles on the road, chaos is created, resulting in environmental and health hazards. With the advent of the digital era, artificial intelligence (AI) and an increase in computing facilities, the intelligent transportation system (ITS) can make the lives of commuters easy and safe by making them better informed and helping them to optimally utilize the available resources. ITS can help in efficient infrastructure usage along with congestion control and road safety. Automated real-time data collection and its analysis is a vital part of any ITS application and will assist in the development of an efficient real-time traffic monitoring system [1] [2]. This system may include traffic flow control, route planning, incident detection, detecting violations, and tracking vehicles.

Vehicle detection is critical in traffic monitoring, as it helps in obtaining real-time data on traffic volume, vehicle class, speed, direction of movement, etc. [3], [4], [5]. The detection of a vehicle is highly dependent on the type of sensor used. A variety of sensing devices are available to sense the presence of a vehicle in real-time [4], [6], [7], [8], [9], [10]. While selecting a suitable sensing device, factors such as application, accuracy, and cost should be taken into account. Presently loop detectors and video cameras are in greater use worldwide for this purpose [11], [12], [13]. However, during congestion and bad weather condition, video cameras face severe difficulty as they are not robust concerning illumination and occlusions (when a small vehicle is behind a big vehicle) [12] [14]. Due to this, inductive loop detectors (ILD) are preferred as a sensing device, especially for conditions where occlusion is a serious issue. ILD′s simplistic hardware design, resulting in a long life span and low-cost, is another reason for its popularity [15]. Difficulty in installation and maintenance, since loop detectors are installed below the road surface, is the major shortcoming of this sensor [10].

Historically loop detectors are in use as traffic sensors from the 1960s [10]. They work on the principle of mutual inductance and can detect the presence and passage of a vehicle [15]. ILD sensor consists of an inductive loop and supporting electronic circuitry to acquire data [3]. Traditional loop designs can detect either small vehicles or large vehicles using distinct loop designs for the corresponding vehicle type. A new loop design proposed by Ali et al. (2012) can detect small as well as large vehicles [16]. Moreover, traditional loop detectors are suitable for lane disciplined vehicular traffic having no parallel movement of vehicles [3], [11], [14]. Since the traffic in many countries, such as India, is less-lane disciplined and heterogeneous, a different loop configuration is required. This issue has been addressed by the multiple inductive loop detector (MILD) system proposed by Ali et al. (2013) [17]. A MILD system consists of multiple loops of smaller dimensions connected in series to cover the lane width. The dimension of the loops is such that only a single two-wheeler can pass on it, whereas a large vehicle may cover two or more loops [16], [17].

When a vehicle passes over the loop, it interacts with the flux created by the electric current flowing through the loop system, and causes a change in the loop inductance. The associated electronic unit of the loop system records this change in loop inductance as the raw output [10] [18]. Thus, the measurements obtained using a loop detector consists of vehicle signatures along with noise caused due to environmental conditions and sensor errors. Therefore, a vehicle occupied region has a vehicle signature superimposed with noise, whereas a vehicle-free region has only noise [10] [19].

Thus, detection of vehicles from loop data necessitate the identification of presence of vehicle and extraction of its signatures from the acquired data using segmentation techniques. Segmentation finds application in many domains such as speech processing to detect the speech and pause area [20], detection of action potentials (APs) in neuroscience [21], license plate detection [22] and, vehicle detection using image processing [23], [24], and vehicle detection from loop data [19], [25].

Earlier studies in vehicle detection using loop detector data sets are limited to lane disciplined traffic [3], [14], [19], [26] and cannot be used directly for lane-less traffic. The main hindrance with MILD data processing is that the measurements across the loops are coupled due to close spacing; making the use of a univariate method to each loop and determining vehicle count erroneous. As the MILD system uses multiple loops to acquire data, the resulting measurements are multi-dimensional. Thus, analysis of the data coming from multiple loops is similar to the analysis of correlated variables in other domains [27]. Under such situations, the solution has been to fuse these readings [28] or to construct a virtual set of readings which are decoupled or decorrelated [29]. For the latter option, a method that decouples these readings while still preserving the vehicle count is required. Following this line of thought, current study proposes to convert these coupled readings to a decoupled set of readings in a virtual world using multivariate data analysis.

Multivariate data analysis can be carried out in different ways depending on the objective. In this work, the objective is to decouple the acquired loop readings and reduce the dimensionality. Dimensionality reduction helps to capture the overall information from the multiple sensors in a lower set of variables or virtual sensors so that the data can be analyzed in that lower-dimensional world [30]. Multi-loop data, the readings of which are coupled with each other, can be converted to either a single virtual loop or many virtual loops that are not coupled with each other, depending on the need [31]. Here, an important point to be mentioned is that the virtual loop data is not necessarily physically interpretable. However, the virtual loop data is not used in this study for understanding or deriving any connection with the physics of the vehicle detection process and hence can still be useful.

This problem of constructing virtually decoupled readings have been studied in-process data analytics, and several solutions have been found, among which the principal component analysis (PCA) is the most popular one. Apart from decoupling, the built-in benefit of PCA is that it gives dimensionality reduction [14], [32], [33]. A standard problem with the use of PCA is that of selecting the appropriate PCs. For example, in signal compression, fault detection, pattern recognition, or dimensionality reduction, the standard criterion that is applied is based on how much variability or the desired feature has been captured by the top few PCs [32], [34]. However, our goal here is to arrive at vehicle count as accurately as possible and hence the requirements are different. For the data sets under consideration, vehicle occupied regions (vehicle signature) are very sparse compared to vehicle-free regions and the noise variance of some of the variables is higher compared to that of others. Therefore, it is necessary to apply a different PC selection strategy. For this purpose, a new PC selection strategy that is contextualized for this application is proposed.

Subsequently, the principal components are individually analysed to identify and detect the vehicle's signatures. For this purpose, a statistical measure of variance, namely, the mean absolute deviation (μAD) based segmentation technique, is selected due to its robustness and sensitivity features [19], [35].

The major contribution of this work is a three-stage online vehicle detection algorithm for MILD data. These stages are listed below:

1) Decoupling of acquired multidimensional data
2) Dimensionality reduction
3) Detection and segmentation of vehicle signatures

Thus, this study proposes an algorithm that is less demanding computationally and data wise, to detect the vehicle, segment the vehicle signatures, and extract the total vehicle count in real-time for less-lane disciplined and heterogeneous traffic scenarios. PCA is used in a unique way to decouple the multi-dimensional measurements and dimensionality reduction in order to reduce the complexity. A novel mechanism is suggested for PC selection suited to this application. Further, the optimal segment size is selected for processing data in real-time to reduce the waiting time for adequate data collection and maintaining acceptable accuracy in vehicle detection. Finally, a mean absolute deviation (μAD) based univariate algorithm is used for vehicle detection, which is immune to outliers and sensitive to signatures/magnetic profiles of different vehicle classes.

The paper is organized as follows. In Section II, the motivation behind this work and the problem formulation is discussed. Section III reviews the necessary theoretical background. Technical details of the proposed methodology for vehicle detection in heterogeneous and lane-less traffic conditions are discussed in Section IV. Insights regarding the conducted experiment and data acquisition framework are also given in Section IV. Experimental results are presented in a step-wise fashion in Section V and the findings are discussed. Finally, Section VI presents the concluding remarks.

II. PROBLEM STATEMENT

The first part of this section demonstrates, using full data set, why the algorithms developed for lane-based traffic are not necessarily suitable for less lane disciplined traffic. For this, the algorithm proposed by Singh et al. [19] for the segmentation of vehicles from single loop system data in lane-based traffic is used for the MILD system data, by treating individual loop as a single loop entity. The bias correction factor (α) and the threshold value (h), that are required for the algorithm, have been calculated by characterizing the noise of each loop separately. Results are presented in Table 1, where L1, L2, and L3 represent loop 1, loop 2, and loop 3 data respectively. This data set consists of two-wheeler,

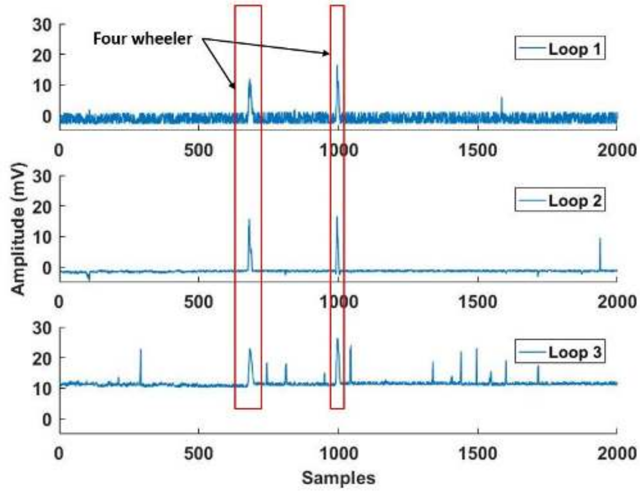


FIGURE 1. A sample MILD data segment.

three-wheeler, and other large vehicles. Using a segment of data Figure 1 illustrates the occupancy of loops by different types of vehicles. However, it can be seen that getting total vehicle count is difficult with this approach, considering the following points:

- A large vehicle can occupy two or more loops at a time, whereas a small vehicle such as a cycle or bike can occupy a single loop.
- A three-wheeler or a four-wheeler vehicle signature detected by individual loops of a MILD system can be of different length due to different tuning parameters of the corresponding loop.
- All 3 loops can be occupied by a four-wheeler or combinations such as 3 two-wheelers or 1 three-wheeler and 1 two-wheeler at any point of time.
- Since loops are placed very near to each other, there is a possibility of partial occupancy of one or more loops.

If the total vehicle count is to be extracted from Table 1 data, then the simple way is to sum the vehicle counts detected by individual loops. Since large vehicles occupy multiple sensor loops, they are counted multiple times while performing the summation. This results in erroneous vehicle count. The total vehicle count extracted using Table 1 is 1411 and the estimated count is 1039, while the true vehicle count is 1123,

TABLE 1. Vehicle detection statistics for sample MILD data segment using univariate data analysis

Loop No.	q	$\hat{q}$	Type I error	Type II error
L1	314	112	202	3
L2	265	204	61	12
L3	832	723	109	18
Total vehicle count	1411	1039	379	33

Note: q - True vehicle count; $\hat{q}$ - Estimated count of correctly detected vehicles ; Type I error - Vehicle is present but not detected; Type II error - Vehicle is not present but detected.

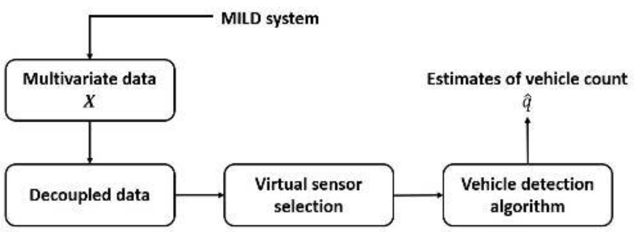


FIGURE 2. Schematic depicting vehicle detection and counting.

showing a mismatch. This example clearly illustrates that a decentralized analysis is not going to give any favorable results. It highlights the need for a multivariate data analysis framework that overcomes the coupled nature of the readings and that it is preferable to work with as few virtual loops as possible as it makes analysis easier, less time-consuming, and easy to visualize the outcome.

Based on these, the main objective of the study can be stated as: Given noisy measurements of a MILD system, detect the presence of a vehicle and extract the total vehicle count ($\hat{q}$).

A single virtual loop can be hypothesized in place of multiple loops in such a way that the output of this virtual loop consists of most of the information associated with multiple loop data. A schematic depicting the problem formulation for vehicle detection is shown in Figure 2. The notations followed are listed in Table 2.

The noisy measurements acquired from the sensor are assumed to be related to the corresponding true values by the following additive noise model

$$x_l\left[k\right] = x_l^*\left[k\right] + e_l\left[k\right], \tag{1}$$

where $x_l\left[k\right]$, $x_l^*\left[k\right]$ are the noisy and noise-free measurements of the l_{th} loop at time k, respectively and $e_l\left[k\right]$ is the error in the measurement of the corresponding loop. It is also assumed that the errors $e_l\left[k\right]$ in the measurements are zero mean and white; that is, stationary and also mutually uncorrelated as

$$E\left\{e_l\left[i\right] e_l\left[j\right]\right\} = 0 \quad \forall \quad i \neq j, \tag{2}$$

TABLE 2. List of symbols

Symbols	Description
L_d	Densely occupied loop
PC	Principal components
x_l^*	Noise-free measurements
x_l	Noisy measurements
e_l	Error in measurements
x_s	Segmented data
q	True vehicle count
$\hat{q}$	Estimated vehicle count
i, j, k	Sample index
N	Sample size of data segment

and there is no significant correlation between errors across loops of MILD system.

A multivariate data analysis based approach is adopted to solve the above problem. Principal component analysis (PCA) is used for constructing virtually decoupled readings from the acquired multidimensional data, $\mathbf{X} = \begin{bmatrix}\mathbf{x_1} & \mathbf{x_2} & \mathbf{x_3}\end{bmatrix}$. Apart from decoupling, the built-in benefit of PCA is that it transforms the raw data into a lower dimension of virtual readings or principal components (PC). This virtual space represents the same information as represented by original raw data. The solution to the PCA problem is given by the eigenvalue decomposition of the covariance matrix ($\frac{\mathbf{1}}{\mathbf{N}}\mathbf{X^T X}$). The principal component is represented as a linear combination of the variables i.e. loops, as

$$\mathbf{PC_j} = a_{j1}\mathbf{x_1} + a_{j2}\mathbf{x_2} + a_{j3}\mathbf{x_3}, \qquad j = 1, 2, 3 \tag{3}$$

where constants a_{j1}, a_{j2}, and a_{j3} are elements of the j_{th} eigenvector. The densely occupied loop (L_d) plays a crucial role while selecting the PC in the virtual domain. L_d can be characterized as the loop which is occupied by the maximum number of vehicles compared to other loops in a fixed duration. Subsequently, vehicle signature is detected using μAD based vehicle detection algorithm from the virtual readings i.e., in the transformed domain. The coming section provides a brief overview of μAD based algorithm and PCA, which are used in this study to process this data.

III. THEORETICAL BACKGROUND

A. μAD BASED ALGORITHM

The mean absolute deviation based algorithm, proposed by Singh et al., is a threshold-based approach and is used in this study for vehicle detection and segmentation [19]. The μAD measure is used as a feature in this algorithm since it is fairly adaptive in capturing the information about the shape and scale of the distribution [36]. The standard deviation of the data is estimated using a sliding window approach. Here, μAD is chosen to estimate the standard deviation. For a segment of data, μAD is calculated using:

$$\mu AD = \alpha \cdot \text{mean}(|\mathbf{x} - \text{median}(\mathbf{x})|), \tag{4}$$

where $\mathbf{x}$ is the vector of observations, and α is a bias correction factor.

As the mean absolute deviation is a biased estimator of standard deviation, a correction factor (α) is used to correct the bias [35]. Data segments corresponding to vehicle-free regions i.e. noise are manually extracted from the historical loop data. Through a statistical analysis of noise segments bias correction factor and threshold value are calculated [19], [35]. Figure 3 shows the noise sample extracted manually from the raw data and its probability density function which is estimated using non-parametric kernel density estimation (KDE). Subsequently, a threshold value (h) is used to perform the thresholding operation to distinguish the vehicle activity sections and vehicle-free sections from the mean absolute deviation data. Segmented data has non-zero values for vehicle occupied region and zero for the remaining

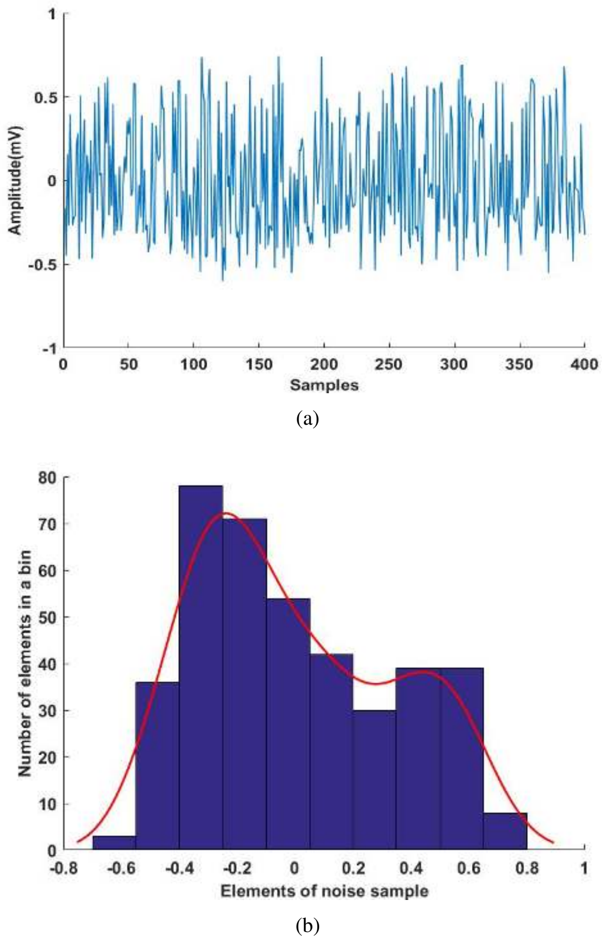


FIGURE 3. Noise analysis (a) Manually extracted vehicle free region, (b) Histogram with kernel distribution fit.

region. Continuous non-zero streams are counted from the segmented data to estimate the total vehicle count. The only constraint of this method is that the data should be unidimensional.

B. PCA-BASED ALGORITHM

Principal component analysis is a well established multivariate statistical analysis technique, mainly used for dimensionality reduction or data compression, without significant information loss and at the same time increases interpretability as a few PCs represent nearly all information in condensed form [29], [33], [37]. The basic concept of PCA is to construct new uncorrelated variables that are linear combinations of the variables present in the given data, preserving most of the information [29]. Suppose $\mathbf{X}$ is an $m \times n$ measurement matrix consisting of m samples of n variables. Measurements of each variable are standardized to have zero mean and unit variance [38]. Correlation matrix ($\mathbf{S}$) of $\mathbf{X}$ can defined as:

$$\mathbf{S} = \frac{\mathbf{1}}{\mathbf{N}}\mathbf{X}^{\mathbf{T}}\mathbf{X}. \tag{5}$$

$\mathbf{S}$ is a square and symmetric matrix whose diagonal elements are the variances of n - variables. Principal component matrix P is defined as:

$$\mathbf{P} = \mathbf{X}\mathbf{V}, \tag{6}$$

where $\mathbf{V}$ is an $n \times n$ square matrix that contains eigenvectors of $\mathbf{S}$. Columns of the matrix $\mathbf{P}$ are known as the principal components. The first principal component is computed by projecting the measurement matrix ($\mathbf{X}$) on the first column of matrix $\mathbf{V}$, which is also known as the coefficient matrix, second principal component is computed by projecting the matrix ($\mathbf{X}$) on the second column of matrix $\mathbf{V}$, and so on. Eigenvalues of $\mathbf{S}$ are arranged in descending order. Thus, the first principal component has maximum information; the second has lesser information than the first PC, and so on. However, there is no guarantee that the PCs corresponding to maximum variance will contain desired features for a specific application [33], [38].

The proposed methodology adopted in this study to extract vehicle signatures from the multidimensional measurements is discussed next.

IV. METHODOLOGY AND EXPERIMENTAL DETAILS

A. METHODOLOGY

Loop detector data consists of vehicle signatures along with noise [10]. To extract the true vehicle signatures from the acquired noisy data, characterization of noise plays a significant role. Noise characterization involves fitting an appropriate distribution on historical data of the vehicle-free region as discussed by Singh et al. [19]. It helps in determining the threshold value to distinguish the vehicle occupied and vehicle-free region and subsequently getting the vehicle signatures [35].

The MILD system setup used in this study consists of three-loops. Hence, the output data is three dimensional. The acquired raw data is decoupled using PCA by projecting it

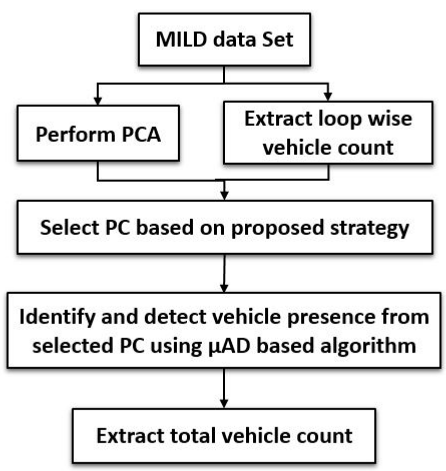


FIGURE 4. Flow chart of the proposed algorithm.

into a new set of orthogonal basis, also known as principal components (PCs) [29]. Since the μAD based algorithm for extracting vehicle count information can be applied only to univariate data, the dimension of the decoupled readings needs to be reduced.

In order to reduce the dimension of the decoupled data in the virtual domain, one of the principal components that has the maximum contribution from the densely occupied loop (L_d) is selected. To find out the L_d, loop-wise vehicle count is extracted using an earlier developed algorithm for vehicle detection from a single loop system [19], by treating the individual loop of the MILD system as a single loop entity. Loop-wise vehicle count data help in identifying the loop, which is occupied by vehicles most of the time, and eventually, this loop is considered as L_d.

The selected univariate data in the virtual domain is further processed using μAD based algorithm to extract total vehicle count information. A threshold is used on mean absolute deviation (μAD) measure to achieve the task of detection and segmentation of vehicle occupied and the vehicle-free region as

$$x_s[k] = \begin{cases} 0 & \text{if } \mu AD[k] < h \\ x[k] & \text{otherwise,} \end{cases} \tag{7}$$

where h is the threshold value. Afterward, the segmented data, $\mathbf{x_s}$, is used to extract the total vehicle count ($\hat{q}$). The proposed algorithm is presented as a flow chart in Figure 4. Its implementation involves the following steps:

1) Get multivariate MILD data as input
2) Determine the densely occupied loop
3) Apply PCA on MILD data for decoupling and dimensionality reduction
4) Select the appropriate principal component for further processing
5) Implement threshold-based μAD algorithm on selected univariate data to detect vehicle presence
6) Use segmented data to estimate total vehicle count

The next subsection gives details of the data acquisition framework.

B. DATA ACQUISITION

The inductive loops are fabricated using a 4 mm common use electric wire as illustrated in Figure 5(a). The experimental setup used for data acquisition in this study consists of the inductive loops and the associated electronic circuitry as shown in Figure 5(b).

The data acquisition platform is developed in NI LabVIEW 2014 software [39]. A multifrequency sinusoidal signal is generated using ArbExpress software and is used as input. A function generator (AFG3022B) is used to reproduce the multifrequency sinusoidal signal. This signal is amplified and used to energize the inductive loops. Measurements are acquired using a 16-bit data acquisition system (DAQ). The change in output voltage corresponding to each frequency is recorded using suitable bandpass filters [17].

(a)

(b)

FIGURE 5. (a) Loops designed for experiment, (b) Experimental setup.

1) Electrical Equivalent Circuit of MILD System

The MILD system used consisted of 3 loops to cover the road width and were connected in series. This configuration enables the system to sense small as well as large vehicles, even in case of parallel vehicle movement. The electrical equivalent circuit of the MILD system is shown in Figure 6. A known resistance R_s is connected in series with the loops to measure the voltage, V_0. The MILD system has three LC circuits with L_1, L_2, and L_3 representing the inductance of the three loops. Resonance frequencies (f_1, f_2 and f_3) of all three LC circuits are calculated theoretically using respective inductance and capacitance values. A multi-frequency sinusoidal input signal, $v_{in}(t)$ is generated using these frequencies and given as input to energize the data acquisition circuit, as illustrated in Figure 7.

The input signal is generated using the mathematical form

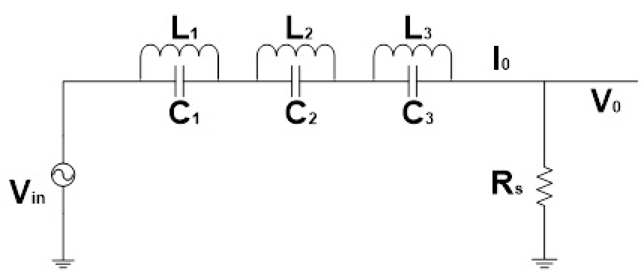
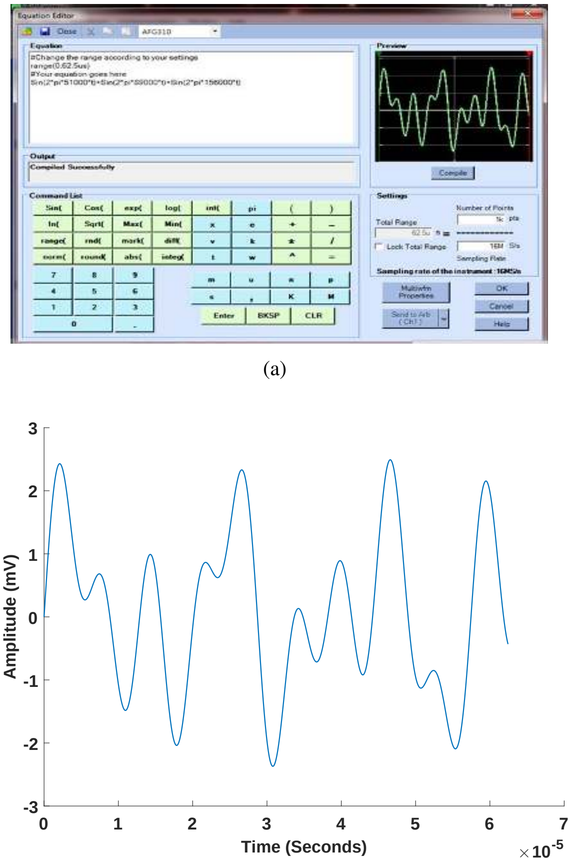


FIGURE 6. Electrical equivalent circuit of series connected multiple loop.



(a)

(b)

FIGURE 7. (a) Snapshot of ArbExpress software used to generated input signal, (b) Multifrequency input signal.

given by equation (8).

$$v_{in}(t) = v_0(\sin 2\pi f_1 t + \sin 2\pi f_2 t + \sin 2\pi f_3 t), \quad (8)$$

where, f_1, f_2, and f_3 are resonance frequencies, defined as,

$$f_1 = \frac{1}{2\pi\sqrt{L_1C_1}}, f_2 = \frac{1}{2\pi\sqrt{L_2C_2}}, \text{and} f_3 = \frac{1}{2\pi\sqrt{L_3C_3}}.$$

Then the output current can be expressed as:

$$I_0(s) = \frac{V_{in}(s)}{Z_1 + Z_2 + Z_3 + Z_{R_s}}, \quad (9)$$

where Z_1, Z_2, and Z_3 represent the equivalent impedance of loop 1, loop 2 and loop 3 respectively. The output voltage across series impedance Z_{R_s} can then be expressed as:

$$V_0(s) = \frac{Z_{R_s}}{Z_1 + Z_2 + Z_3 + Z_{R_s}} V_{in}(s), \quad (10)$$

For the current study, data is collected for nearly 4 hours in a heterogeneous and lane-less traffic condition. A total of 1123 vehicle signatures are collected, which includes cycle, bike, auto, light commercial vehicle (LCV), car, bus, and truck signatures. Video recording of the complete data acquisition process is also done to verify the results. Snapshots of acquired data are shown in Figure 8.

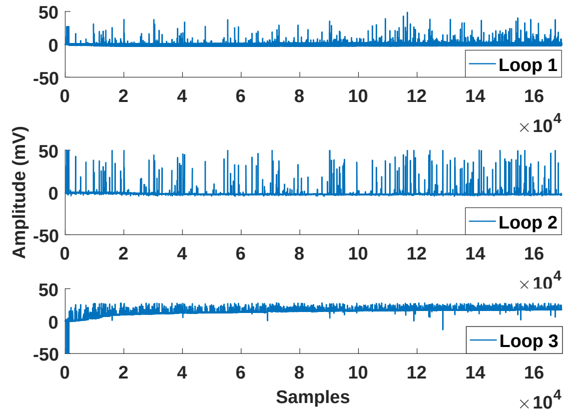


FIGURE 8. Acquired raw data illustrating vehicle signature.

Here, it is important to mention that the two-wheeler generally occupies a single loop, a three-wheeler occupies two loops, whereas four-wheeler or bigger vehicles occupy three loops. It is assumed that while crossing the loops, vehicles are not accelerating or decelerating and vehicle signatures are time-invariant. The next section presents the results and analyses the findings.

V. RESULTS AND DISCUSSION

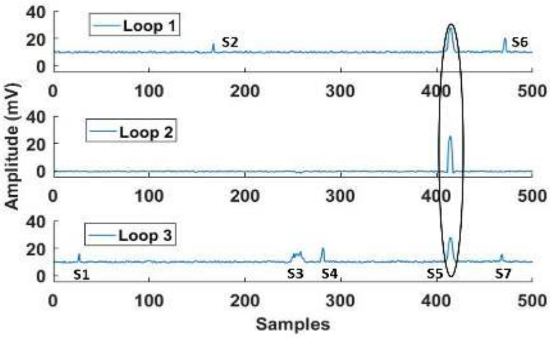
The proposed algorithm has been used for the detection of vehicle signatures in lane-less traffic using the MILD system. To begin with, in the first subsection, a case study is presented which explains the importance of decoupling in MILD data processing during the extraction of vehicle signatures. In the next subsection, a novel PC selection strategy is suggested suiting this application. The effect of segment size on vehicle count accuracy was evaluated and is presented in subsection V-C. The success of the algorithm is also evaluated on the data sets occupied by different classes of vehicles and associated results are presented in subsection V-D.

A. A CASE STUDY ILLUSTRATING THE IMPACT OF DECOUPLING ON MILD DATA PROCESSING

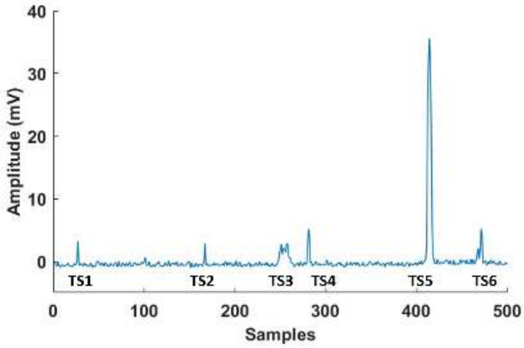
Heterogeneous traffic consists of two-wheelers, four-wheelers, and other large vehicles. When data is acquired using the MILD system two-wheeler signatures are captured by only one loop while in the case of a four-wheeler or other large vehicles all three loops capture the signature at the same time. When vehicle count is extracted using this data, a four-wheeler is counted multiple times due to the coupled nature of measurements. For this, PCA-based decoupling is done. With the help of an example, the significance of decoupling is illustrated next.

Consider a sample data set that consists of a total of 7 vehicle signatures as shown in Figure 9(a). This data segment consists of 1 four-wheeler (S5) and 6 two-wheelers (S1, S2, S3, S4, S6, and S7). Signatures, S6 and S7, represent nearly parallel moving two-wheelers. PCA is used to de-

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3120470, IEEE Access



(a)



(b)

FIGURE 9. (a) Sample data, (b) Transformed data in virtual domain.

couple the raw data. The appropriate variable is selected in the virtual domain and shown in Figure 9(b). Out of seven vehicle signatures, six signatures decoupled successfully and one signature is missed. The four-wheeler signature (S5) is successfully decoupled and indicated as TS5 in Figure 9(b). Two-wheeler signatures S6 and S7, which are partially overlapping due to parallel movement, are superimposed in the virtual domain and are represented as TS6, resulting in the loss of one signature. How PCA helps in dimensionality reduction will be discussed next.

B. PC SELECTION STRATEGY

A PC selection is proposed for this specific application to achieve the highest count accuracy. Four raw data segments of sample size 1000 are considered to explain this strategy. One of the data segments is shown in Figure 10 for illustration purposes. From this figure, it can be easily seen that the vehicle occupied regions are very sparse in the first loop.

Principal component coefficients are calculated using PCA and are presented in Table 3. Each column of the table contains coefficients for one principal component (PC), and the columns are arranged in descending order of their variance. Here, unit scaled principal component coefficients i.e., eigenvectors, represent the directions of the new orthogonal feature space, and eigenvalues give their magnitude. The projection of a segment of the raw data onto the principal

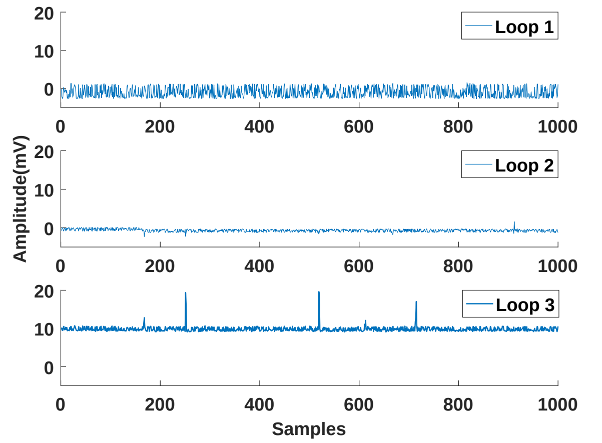


FIGURE 10. Raw data segment (Set 1).

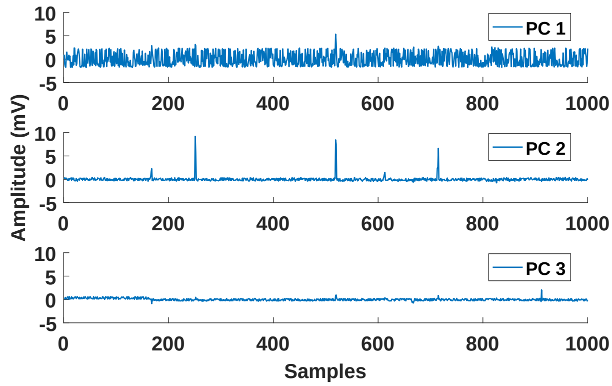


FIGURE 11. Projection of the raw data segment (Set 1) onto the principal component axes.

component (PC) axes are shown in Figure 11.

For the data sets under consideration, the noise variance of loop 1 data is much higher compared to other loop data, making the traditional PC selection strategy impractical. Accurate extraction of vehicle count is the goal of this work and hence our desired features are vehicle signatures. From the visual analysis of Figure 11, it is obvious that PC 1, if PC is selected with traditional approach, is not very useful as it contains very few signatures in comparison to other PCs. Therefore, in order to achieve the highest vehicle count accuracy, a different PC selection strategy is proposed. Loop-wise

TABLE 3. Principal component coefficients of data segments

	(a) Set 1			(b) Set 2		
	PC 1	**PC 2**	**PC 3**	**PC 1**	**PC 2**	**PC 3**
Loop 1	0.9162	-0.3789	0.1303	0.4209	0.8109	-0.4066
Loop 2	-0.1805	-0.1000	0.9785	0.7640	-0.5585	-0.3229
Loop 3	0.3577	**0.9200**	0.1601	0.4889	0.1747	**0.8546**
	(c) Set 3			(d) Set 4		
Loop 1	0.4188	0.8109	-0.4086	0.5214	0.7903	0.3218
Loop 2	0.6500	-0.5819	-0.4887	0.2475	-0.5009	0.8293
Loop 3	0.6341	0.0610	**0.7708**	**0.8166**	-0.3527	-0.4568

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3120470, IEEE Access

TABLE 4. Loop wise estimated vehicle count ($\hat{q}$)

Data set	Loop 1	Loop 2	Loop 3
1.	0	3	9
2.	5	5	6
3.	2	4	7
4.	4	7	10

TABLE 5. Selected PCs

Data set	PCs Before filtering	PCs After filtering
1.	2	3
2.	3	3
3.	3	3
4.	1	2

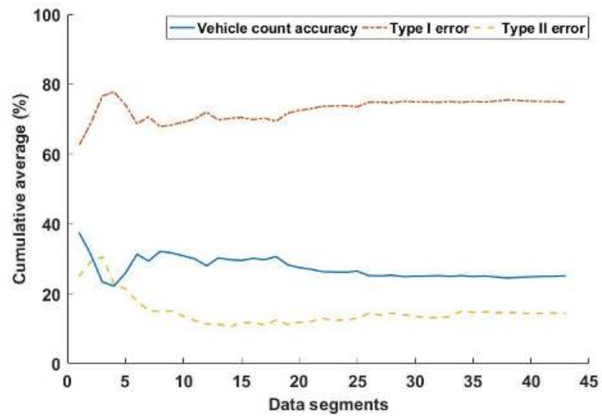


FIGURE 12. Performance of the proposed algorithm with traditional PC selection strategy.

vehicle count information helps in identifying the densely occupied loop and, in turn, the selection of an appropriate PC. For individual loops, vehicle count is calculated using μAD based segmentation algorithm and presented in Table 4. Based on vehicle occupancy data, as given in Table 4, the densely occupied loop (L_d) is identified. Among these projections, as shown in Figure 11, one with maximum contribution from the densely occupied loop is selected using Table 3. Here, a pre-filtering operation is also performed using a moving average filter on the loop data to see the effect of noise on PC selection. On filtered data, PCA is performed and the selected PCs for different data segments are shown in Table 5. It can be seen that PC 1 is still not the preferred principal component for further processing to detect vehicle signature.

Both traditional and newly proposed PC selection strategy is implemented on complete data and the results are presented in Table 6, which signifies the importance of the proposed PC selection strategy. The performance of the proposed algorithm is evaluated using three metrics, namely, accuracy, Type I and Type II error. These metrics are graphically shown for all data segments in Figure 12. The coming section discusses the effect of sample size on vehicle count accuracy.

C. SELECTION OF DATA SEGMENT LENGTH

The sample size (N) of data segments plays a vital role in the extraction of traffic variables. A large data segment size increases the vehicle count accuracy along with computational time. Thus there is a trade-off between count accuracy and computational time. Keeping this in mind, data segments of sizes 1000, 2000, and 3000 are considered for evaluation. Value of N larger than 3000 results in large computational time, which is not advisable for field application.

Twelve raw data segments, four each of sample sizes of 1000, 2000, and 3000, are randomly selected. One of the data segments of sample size 1000 is shown in Figure 10 for illustration. Actual vehicle counts were manually extracted from the recorded video for corroborating the results.

All data segments are processed using the proposed algorithm. Raw data is decoupled and transformed from multi-dimension space to a lower dimension using the PCA algorithm. Subsequently, the μAD based algorithm is applied to process the selected PC, which gives the total vehicle count. Type I and Type II errors are calculated to evaluate the accuracy of the proposed algorithm.

The procedure of decoupling, selecting an appropriate PC

TABLE 6. Vehicle detection statistics for different PC selection strategy

Metrics	Traditional (%)	Proposed (%)
Accuracy	24.31	90.38
Type 1 error	75.69	9.83
Type 2 error	16	7.64

TABLE 7. Vehicle detection statistics (N=1000)

Data Set	PC	q	q̂	Type I error	Type II error
1.	2	6	5	1	1
2.	3	5	4	1	3
3.	3	5	5	0	8
4.	1	14	8	6	0
			80.12 %	26.49 %	30.27 %

TABLE 8. Vehicle detection statistics (N=2000)

Data Set	PC	q	q̂	Type I error	Type II error
1.	3	11	9	2	0
2.	1	19	14	5	0
3.	3	18	13	5	3
4.	2	21	16	5	1
			75.98 %	29.65 %	6.16 %

TABLE 9. Vehicle detection statistics (N=3000)

Data Set	PC	q	q̂	Type I error	Type II error
1.	3	16	15	1	1
2.	3	32	25	7	0
3.	2	26	21	5	1
4.	3	27	27	0	12
			88.16 %	14.25 %	10.39 %

TABLE 10. Class wise vehicle detection accuracy

Vehicle class	q	q̂	Accuracy (%)
Cycle, Motorbike	979	873	89.17
Auto	16	14	87.5
LCV	7	7	100
Car	106	106	100
Bus, Truck	15	15	100
Total	1123	1015	90.38

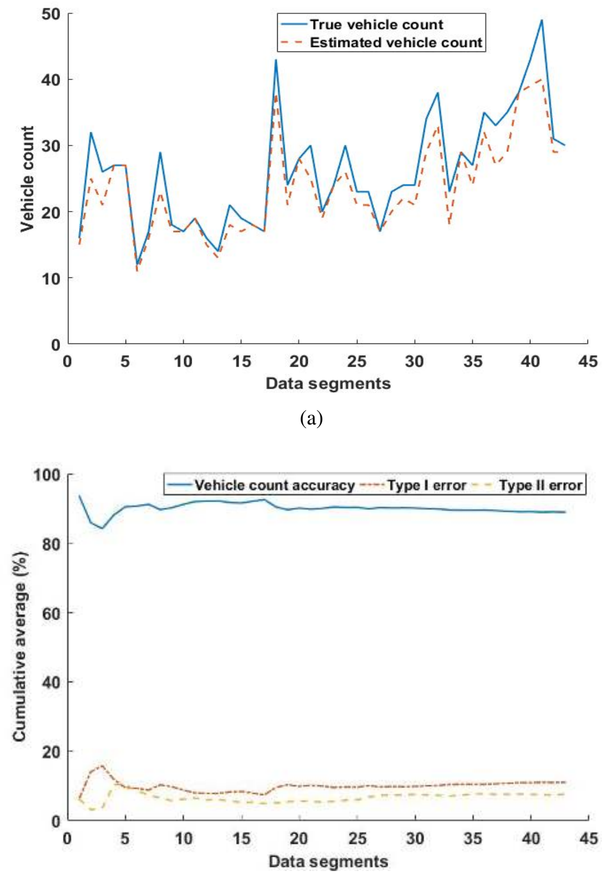
and using μAD to calculate the vehicle count is repeated on other data segments. Vehicle count results for the different data segments of sample size 1000, 2000, and 3000 are listed respectively in Table 7, 8, and 9.

From Table 7, 8 and 9, it can be seen that segments with sample size 3000 have the highest vehicle count accuracy and Type I and Type II error rate is also moderately low, which makes it appropriate sample size for processing large data. The optimal sample size of 3000 is still high, considering computational time requirement and need to be reduced in the future by improving the proposed algorithm.

Subsequently, the algorithm is implemented on the complete data set for heterogeneous and lane-less traffic. Class wise vehicle detection accuracy are presented in Table 10. It can be observed from the table that two-wheeler vehicles are the major contributor to detection error. It is because these signatures are not consistent. These inconsistencies in vehicle signatures are due to different designs and materials, such as metal and fiber, used in their manufacturing. Out of the total 1123 vehicle signatures, 1015 are identified correctly with Type I error 108 and Type II error 84 by this method. Figure 13 shows the performance of the proposed algorithm. The results of this study are compared, with earlier works on heterogeneous less lane-disciplined traffic, to validate the performance, as shown in Table 11. Ali et al. [25], which used data from the MILD sensor for similar traffic condition, and one of the most recent studies from similar traffic conditions, though using different sensor [12], are used in this comparative study.

The use of multiple PCs to improve the vehicle count accuracy is not attempted in this work as it will increase the time taken to do analysis. This approach will also make the analysis more complex since a univariate algorithm has been used for vehicle detection. In the future, a multivariate vehicle detection algorithm will be developed that can be implemented directly on the acquired multivariate raw data, eliminating the requirement of univariate data for the currently proposed algorithm. Some of the limitations of the proposed method are:

1) To calculate the threshold value, using noise characterization, manual intervention is required to identify the vehicle-free region. However, this is a one-time process and hence does not affect the automated counting process.
2) If there is any parallel movement of vehicles, there is a possibility of missing vehicle signatures during the decoupling of the multivariate raw data, which needs to be addressed in the future.



(a)

(b)

FIGURE 13. Performance of the proposed algorithm on real-time field data (a) actual Vs estimated vehicle count, (b) with new PC selection strategy.

The next subsection will discuss the performance of the proposed algorithm on data sets occupied by different vehicle classes.

TABLE 11. Comparison of vehicle detection methods for heterogeneous and Less lane disciplined traffic.

Feature Set	Ali [25]	Satyanarayana [12]	Proposed
Sensors	MILD	Camera and LiDAR	MILD
Data set (Vehicles)	372	4507	1123
Measure	Inductive signature	Video and Binary image	Inductive signature
Method	Amplitude based	Binary image extraction	μAD & PCA
Accuracy rate (%)	88.17	98, 91.3	90.38
Cost	Low	High	Low
Challenges	Installation and maintenance	Illumination and occlusion	Installation and maintenance

Note:- μAD: mean absolute deviation.

TABLE 12. Vehicle detection statistics

Data Set	q (TW+FW)	$\hat{q}$ (%)	Type I error (%)	Type II error (%)
1.	26 (26+0)	21 (80.77)	5 (22.73)	1 (4.55)
2.	15 (0+15)	15 (100)	0 (0)	0 (0)
3.	16 (12+4)	15 (93.75)	1 (6.25)	1 (6.25)

Note:- TW: two-wheeler; FW: four-wheeler.

D. PERFORMANCE EVALUATION OF PROPOSED ALGORITHM ON THE DATA SEGMENTS OCCUPIED BY DIFFERENT CLASSES OF VEHICLES

Vehicle count accuracy for data segments, occupied by different types of vehicles, are evaluated using the proposed method, and results are presented in Table 12. Here, three cases are considered: only two-wheeler, only four-wheeler, and a mix of two-wheeler and four-wheeler.

The first data set consists of only two-wheelers. For this data set, due to parallel movement, some of the two-wheeler signatures are superimposed in the virtual domain resulting in the loss of vehicle signatures. In this case, vehicle detection accuracy is the least. When a data segment is occupied by only four-wheelers, vehicle detection accuracy is highest as explained using the second data set. Here, complete decoupling of four-wheeler vehicle signatures in the virtual domain result in the highest accuracy. The third data set consists of both two-wheelers and four-wheelers. Hence, the vehicle count accuracy of the third data set is in between the first and second data sets. The time complexity aspect of the proposed algorithm is discussed in the next subsection.

E. PROCESSING TIME

For this study, the system used had the following configuration: Intel(R) Core(TM) i7-4770 CPU @ 3.40-GHz processor and 16-GB RAM, and the OS is 64-bit Windows 10 Pro. Algorithms are implemented using the MATLAB platform. The processing time required to run the proposed algorithm is obtained by averaging the execution time for 1000 runs. The execution time of the algorithm, for the accurate extraction of vehicle count from a segment of MILD data, is "0.18 seconds". To estimate the parameters, correction factor (α) and a threshold value (h), the algorithm took "0.15 seconds".

VI. CONCLUSION

This study proposed an algorithm to detect the vehicle signatures from MILD system data for the less-lane disciplined and heterogeneous traffic scenario and extract the total vehicle count. A threshold-based mean absolute deviation (μAD) algorithm has been used to achieve this task of vehicle signature detection, after decoupling the measurements and reducing the MILD data dimension using PCA. The significance of the proposed PC selection strategy compared to the traditional approach is also illustrated on the complete data set for this application. Finally, the efficacy of the proposed algorithm is demonstrated on real-time field traffic data consisting of 1123 vehicle signatures. The proposed algorithm gave an accuracy of 90.38 % in vehicle count with moderate Type I and Type II error of 9.83 % and 7.64 % respectively.

Further, the performance of the proposed algorithm is evaluated using data segments occupied by different classes of vehicles. The highest vehicle count accuracy is achieved for data segments occupied by only four-wheeler, compared to the cases of data segments occupied by only two-wheeler or a mix of two-wheeler and four-wheeler. Future research directions may include improving the accuracy of the proposed algorithm with minimal requirement of historical data and can be extended even further to the extraction of classified vehicle count.

ACKNOWLEDGMENT

The authors would like to acknowledge the Connected Intelligent Urban Transportation Lab, IIT Madras, India for supporting the data collection. Special gratitude goes to Mr. Arun and Ms. Deepa for their help during field data collection.

REFERENCES

[1] M. Won, "Intelligent traffic monitoring systems for vehicle classification: A survey," *IEEE Access*, vol. 8, pp. 73 340–73 358, 2020.

[2] W. Balid, H. Tafish, and H. H. Refai, "Intelligent vehicle counting and classification sensor for real-time traffic surveillance," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 6, pp. 1784–1794, 2017.

[3] Y.-K. Ki and D.-K. Baik, "Vehicle-classification algorithm for single-loop detectors using neural networks," *IEEE Transactions on Vehicular Technology*, vol. 55, no. 6, pp. 1704–1711, 2006.

[4] J. Gajda and M. Mielczarek, "Automatic vehicle classification in systems with single inductive loop detector," *Metrology and Measurement Systems*, vol. 21, no. 4, pp. 619–630, 2014.

[5] S.-T. Jeng, L. Chu, and S. Hernandez, "Wavelet–k nearest neighbor vehicle classification approach with inductive loop signatures," *Transportation research record*, vol. 2380, no. 1, pp. 72–80, 2013.

[6] X. Chen, X. Kong, M. Xu, K. Sandrasegaran, and J. Zheng, "Road vehicle detection and classification using magnetic field measurement," *IEEE Access*, vol. 7, pp. 52 622–52 633, 2019.

[7] H. Dong, X. Wang, C. Zhang, R. He, L. Jia, and Y. Qin, "Improved robust vehicle detection and identification based on single magnetic sensor," *IEEE Access*, vol. 6, pp. 5247–5255, 2018.

[8] H. Tayara, K. G. Soo, and K. T. Chong, "Vehicle detection and counting in high-resolution aerial images using convolutional regression neural network," *IEEE Access*, vol. 6, pp. 2220–2230, 2017.

[9] S. Taghvaeeyan and R. Rajamani, "Portable roadside sensors for vehicle counting, classification, and speed measurement," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 1, pp. 73–83, 2013.

[10] L. A. Klein, M. K. Mills, and D. R. Gibson, "Traffic detector handbook: -volume i," Tech. Rep., 2006.

[11] J. Gajda, R. Sroka, M. Stencel, A. Wajda, and T. Zeglen, "A vehicle classification based on inductive loop detectors," in *Instrumentation and Measurement Technology Conference, 2001. IMTC 2001. Proceedings of the 18th IEEE*, vol. 1. IEEE, 2001, pp. 460–464.

[12] G. Satyanarayana, S. Majhi, and S. K. Das, "A vehicle detection technique using binary images for heterogeneous and lane-less traffic," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–14, 2021.

[13] M. S. Chauhan, A. Singh, M. Khemka, A. Prateek, and R. Sen, "Embedded cnn based vehicle classification and counting in non-laned road traffic," in *Proceedings of the Tenth International Conference on Information and Communication Technologies and Development*, 2019, pp. 1–11.

[14] S. Meta and M. G. Cinsdikici, "Vehicle-classification algorithm based on component analysis for single-loop inductive detector," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 6, pp. 2795–2805, 2010.

[15] R. L. Anderson, "Electromagnetic loop vehicle detectors," *IEEE Transactions on Vehicular Technology*, vol. 19, no. 1, pp. 23–30, 1970.

[16] S. S. M. Ali, B. George, L. Vanajakshi, and J. Venkatraman, "A multiple inductive loop vehicle detection system for heterogeneous and lane-less traffic," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 5, pp. 1353–1360, 2011.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3120470, IEEE Access

[17] S. S. M. Ali, B. George, and L. Vanajakshi, "An efficient multiple-loop sensor configuration applicable for undisciplined traffic," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 3, pp. 1151–1161, 2013.

[18] J. J. Lamas-Seco, P. M. Castro, A. Dapena, and F. J. Vazquez-Araujo, "Sidivs: Simple detection of inductive vehicle signatures with a multiplex resonant sensor," *Sensors*, vol. 16, no. 8, p. 1309, 2016.

[19] N. K. Singh, L. Vanajakashi, and A. K. Tangirala, "Segmentation of vehicle signatures from inductive loop detector (ILD) data for real-time traffic monitoring," in *2018 10th International Conference on Communication Systems & Networks (COMSNETS)*. IEEE, 2018, pp. 601–606.

[20] M. Marzinzik and B. Kollmeier, "Speech pause detection for noise spectrum estimation by tracking power envelope dynamics," *IEEE Transactions on Speech and Audio Processing*, vol. 10, no. 2, pp. 109–118, 2002.

[21] A. Quotb, Y. Bornat, and S. Renaud, "Wavelet transform for real-time detection of action potentials in neural signals," *Frontiers in neuroengineering*, vol. 4, 2011.

[22] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, V. Loumos, and E. Kayafas, "A license plate-recognition algorithm for intelligent transportation system applications," *IEEE Transactions on Intelligent transportation systems*, vol. 7, no. 3, pp. 377–392, 2006.

[23] D. Mittal, A. Reddy, G. Ramadurai, K. Mitra, and B. Ravindran, "Training a deep learning architecture for vehicle detection using limited heterogeneous traffic data," in *2018 10th International Conference on Communication Systems & Networks (COMSNETS)*. IEEE, 2018, pp. 589–294.

[24] S. Gupte, O. Masoud, R. F. Martin, and N. P. Papanikolopoulos, "Detection and classification of vehicles," *IEEE Transactions on intelligent transportation systems*, vol. 3, no. 1, pp. 37–47, 2002.

[25] S. S. M. Ali, N. Joshi, B. George, L. Vanajakshi *et al.*, "Application of random forest algorithm to classify vehicles detected by a multiple inductive loop system," in *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on*. IEEE, 2012, pp. 491–495.

[26] G. K. V. Yogesh and L. Vanajakshi, "Automated tolling solution with novel inductive loop detectors using machine learning techniques," *Journal of Computing in Civil Engineering*, vol. 32, no. 6, p. 04018046, 2018.

[27] J. F. Hair, W. C. Black, B. J. Babin, R. E. Anderson, R. L. Tatham *et al.*, *Multivariate data analysis*. Prentice hall Upper Saddle River, NJ, 1998, vol. 5, no. 3.

[28] D. L. Hall and J. Llinas, "An introduction to multisensor data fusion," *Proceedings of the IEEE*, vol. 85, no. 1, pp. 6–23, 1997.

[29] I. T. Jolliffe and J. Cadima, "Principal component analysis: a review and recent developments," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 374, no. 2065, p. 20150202, 2016.

[30] L. Van Der Maaten, E. Postma, and J. Van den Herik, "Dimensionality reduction: a comparative," *J Mach Learn Res*, vol. 10, no. 66-71, p. 13, 2009.

[31] Q. Zhang and G. Gao, "Grasping point detection of randomly placed fruit cluster using adaptive morphology segmentation and principal component classification of multiple features," *IEEE Access*, vol. 7, pp. 158 035–158 050, 2019.

[32] I. T. Jolliffe, "Principal components in regression analysis," in *Principal component analysis*. Springer, 1986, pp. 129–155.

[33] Y. Dai, J. Guan, W. Quan, C. Xu, and H. Zhang, "PCA - based dimensionality reduction method for user information in universal network," in *2012 IEEE 2nd International Conference on Cloud Computing and Intelligence Systems*, vol. 1. IEEE, 2012, pp. 70–74.

[34] C. M. Bishop, *Pattern recognition and machine learning*. springer, 2006.

[35] S. Kathirmani, A. Tangirala, S. Saha, and S. Mukhopadhyay, "Online data compression of mfl signals for pipeline inspection," *NDT & E International*, vol. 50, pp. 1–9, 2012.

[36] E. A. Elamir, "Mean absolute deviation about median as a tool of explanatory data analysis," in *Proceedings of the World Congress on Engineering*, vol. 1, 2012.

[37] J. Lever, M. Krzywinski, and N. Altman, "Points of significance: Principal component analysis," *Nature Methods*, vol. 14, no. 7, pp. 641–642, 6 2017.

[38] L. Xu, Y. Yan, S. Cornwell, and G. Riley, "Online fuel tracking by combining principal component analysis and neural network techniques," *IEEE Transactions on Instrumentation and Measurement*, vol. 54, no. 4, pp. 1640–1645, 2005.

[39] C. Elliott, V. Vijayakumar, W. Zink, and R. Hansen, "National instruments labview: a programming environment for laboratory automation and measurement," *JALA: Journal of the Association for Laboratory Automation*, vol. 12, no. 1, pp. 17–24, 2007.

MR. NIRAJ KUMAR SINGH received the B.E. and M.Tech. degrees in electronics and communication engineering from the Sant Longowal Institute of Engineering & Technology (SLIET), Longowal, Punjab. He is currently a Ph.D. research scholar with Indian Institute of Technology Madras, Chennai, India. His research interests include data analytics and intelligent transportation system.

DR. ARUN K. TANGIRALA graduated with a Bachelors in Chemical Engineering from the Indian Institute of Technology Madras, India in 1996 and a Ph.D. degree in process control and monitoring from the University of Alberta, Canada in 2001. He is currently a Professor with the Department of Chemical Engineering, IIT Madras. His research group conducts cutting-edge research in process systems engineering, identification, soft sensing and applied data science. Dr. Tangirala is a recipient of various teaching and research awards, and is the author of a comprehensive classroom text titled "Principles of System Identification: Theory and Practice", published by CRC Press.

DR. LELITHA DEVI VANAJAKSHI is a Professor in the Transportation Division of the Department of Civil Engineering at Indian Institute of Technology Madras, Chennai, India. She holds a Ph. D. in Transportation Engineering from Texas A.M University, USA. Her teaching and research interests are in the general area of transportation systems with emphasis on traffic flow modeling, traffic operations, and Intelligent Transportation systems.