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Multi-lane Vehicle Detection Method based on Magneto-resistive Sensors

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Abstract: In traffic information acquisition system, vehicle detection method based on magneto-resistive sensors is more convenient and cheaper than traditional methods from the perspectives of installation and maintenance. This paper focuses on the magneto-resistive vehicle detection method for multi-lane scenery. A single-node vehicle detection algorithm (SNVD) based on multiple magnetic detection features is proposed to deal with dense traffic and low velocity vehicles. Moreover, a multi-lane vehicle detection method (MLVD) is proposed to solve the false detection by trans-lane and adjacent-lane vehicles, which is based on the combination of SNVD, vehicle position recognition and multi-node integration. With acquisition data on real road, SNVD is proved to be adaptable to different traffic situations. Test results also show the detection accuracy of MLVD is above 99%, the method features strong robustness and good scalability, which is applicable for urban multi-lane sceneries.

Keywords: magneto-resistive sensors, vehicle detection, multi-lane, vehicle position recognition, detection fusion

1. Introduction

With rapid development of intelligent transportation industry, traffic information acquisition applications become more and more common. However, traditional detection technologies such as video, induction coils, radar and ultrasonic have been applied in a limited scale, and most of these technologies are cost expensive, with complexity in installation and maintenance [1]. In recent years, the emerging magneto-resistive detection based on wireless sensor networks has attracted much attention due to its compact size, low costs, high reliability, ease of installation and maintenance [2].

Within a few kilometers range, the geomagnetic field can be seen as constant uniform. Vehicles containing ferromagnetic materials can lead to offset or disturbance on background geomagnetic field [3], making it possible to detect the vehicle presence by sensing magnetic field changes. In normal method, one sensor node is deployed in the middle of each single lane, and for multiple lanes the total traffic flow equals the sum of flow on each lane [4-5]. Unfortunately, there exist two problems to be solved under multi-lane sceneries.

1) Adjacent-lane vehicles. Larger vehicles on adjacent lanes may induce large enough signals to result in false detection on current lane [6].

2) Trans-lane vehicles. Vehicles travelling between two lanes may be detected by two nodes simultaneously and lead to redundant results of total flow. Meanwhile, vehicles also may be missed by both nodes.

This paper is organized as follows. Section II introduces the related work. Section III presents the framework of MLVD. Section IV describes the detection algorithms on distributed sensor nodes. Section V demonstrates the integration of multi-node detection. Section VI gives the experimental results and analysis. Conclusions are presented in Section VII.

2. Related Work

At present, many researches about magneto-resistive vehicle detection have been carried out. Researchers from University of Berkeley proposed Adaptive Threshold Detection Algorithm (ATDA) [7]. ATDA is based on threshold and finite state machine (FSM), realizing detection with high efficiency and real-time performance. Based on ATDA, improvements have been made on detection features selection, drift elimination, threshold setting and FSM design [8-12]. Several algorithms introduced correlation similarity to achieve better signal-noise ratio at the expense of decreasing real-time performance and increasing computational complexity [13, 14]. Most algorithms were proved to be suitable for medium dense traffic in single-lane sceneries, yet the accuracy for dense traffic had not been evaluated.

Single-lane detection algorithms can’t be applied to multiple lanes directly due to the adjacent-lane and trans-lane vehicles [15]. A fusion method for bidirectional two-lane scenery was introduced in [16]. The method identifies adjacent-lane vehicles based on magnetic signal strength and driving direction, the detection accuracy rate is 93%. In [17], adjacent-lane vehicles are distinguished based on magnetic signal attenuation characteristics and Support Vector Machine (SVM) classification. The method can detect one of multiple lanes with accuracy rate of 99%. However, these methods can’t deal with trans-lane vehicles. Besides, the methods must deploy sensor nodes at roadside, so they can't be expanded to sceneries of more than two lanes.

3. Framework of Detection System

In this section, the framework of MLVD is introduced to achieve better detection performance in multi-lane sceneries. Nodes layout of MLVD is shown in Fig.1. Based on nodes layout of the normal methods, one added sensor node (SN) is deployed on the boundary line between every two lanes. When the number of lanes is N, the total nodes number is 2N-1. The access point node (AP) provides time synchronization for SNs and integrates detection results from all SNs. Generally, the lane is 3~3.75m wide and the vehicle width range from 1.5m to 2.5m. To avoid interference caused by vehicles in adjacent lanes, SNs are set at a small detection radius. It's ensured that a vehicle traveling across nodes array will be detected by at least one SN.

Fig.2 shows the processing procedures of MLVD, which mainly consists of single-node vehicle detection algorithm SNVD, position recognition and multi-node results integration.

SNs process magnetic sampling data, run SNVD algorithm to identify arriving and departure time of each vehicle. Position recognition algorithm is used to classify detected vehicles into two situations, i.e. traveling over the SN or traveling from side of SN. By extracting features of signal magnitude and peak-valleys, two traveling situations can be decided by a trained classifier. Both SNVD and position recognition algorithms are implemented on single SN to guarantee efficiency and real-time performance.

Vehicle detection results about time and position are packed into records and sent to AP for matching and fusion. Records from several SNs with approximate time information may indicate more than one vehicle passing. According to restrictions of vehicle position, nodes layout and vehicle width, a fusion algorithm will decide the actual number of vehicles traveling across nodes array.

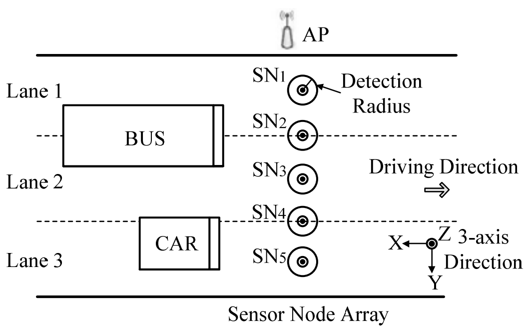

Fig.1. Nodes layout scheme of MLVD

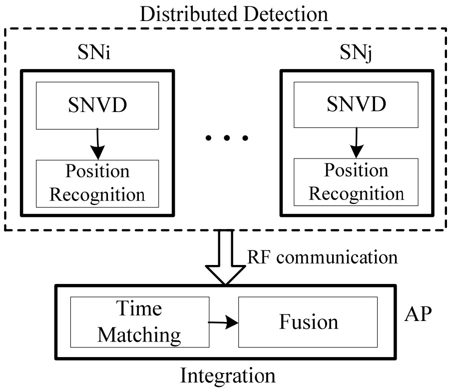

Fig.2. Procedures of multi-lane detection

4. Distributed Detection

4.1 Single-node Vehicle Detection

Considering the limited computing ability and battery power of SNs, vehicle detection algorithm must be lightweight in complexity. SNVD algorithm is proposed based on the state machine of ATDA algorithm, which is given in Fig.3. SNVD processes 3-axis sampling data once after sampling. The moving average filter is used to smooth the magnetic signal, and the baseline tracing is designed based on the moving median filter.

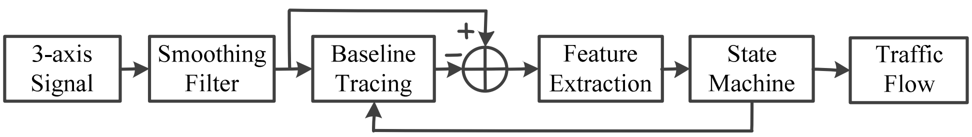

Fig.3. Single-node detection algorithm procedure

Detection feature reflects the magnetic signal changing caused by vehicles. In SNVD, more than one feature is extracted for detection. The net signal components of x, y, z are obtained by subtracting baseline from the raw signals. Component z decreases quickly when vehicle is leaving. Since x and y are always significant even when the vehicle is far away from the SN, thus, they are divided by a factor n to facilitate splitting the signals of successive close vehicles. Component dx, dy, dz are forward difference of 3-axis signals, which reflect the vehicle moving information with less signal drift. The threshold comparison conditions are given:

$$\max(z, x/n, y/n) \geq TH1 \tag{1}$$

$$\max(dx, dy, dz) \geq TH2 \tag{2}$$

In Eq.(1) and Eq.(2), TH1 and TH2 are both empirical thresholds upon analysis of actual signals. Either Eq.(1) or Eq.(2) is met, the input of state machine is true, otherwise, it is false.

4.2 Vehicle position recognition

As one or more SNs may detect vehicles at one point, the vehicle position information on each of these nodes can be gathered to help judging the real number of vehicles. So, the vehicle position recognition is introduced, and it will assist detecting the trans-lane and adjacent-lane vehicles.

As magnetic field points to the ground roughly in northern hemisphere, ferromagnetic materials gathering magnetic induction lines will enhance the vertical magnetic component. Consequently, when the vehicle travels over the SN, the signals of vertical Z-axis tend to be unidirectional. Besides, the signal has more significant magnitude and more peak-valleys since the vehicle is close to SN. However, when the vehicle travels from side of SN, the signal characteristics are opposite.

Two features of Z-axis signals are extracted for vehicle position recognition. One is the mean value of negative sample points (zneg); the other is the number of waveform peak-valleys (zpv), while small peak-valleys are removed. Upon feature extraction and normalization, Fisher linear discriminant analysis (FLDA) is used to train a class boundary function for recognition [18]. In FLDA, samples in D-dimensional space (D≥2) are projected onto 1-dimensional space, finding the best projection direction to get maximum between-class dispersion and minimum within-class dispersion.

In training, 138 vehicle samples are selected, which includes 51 samples travelling over SN and 87 samples travelling from side of SN. A training classification accuracy rate of 99% is achieved in results.

After detection and feature extraction in SNs, vehicle position can be recognized using the class boundary function trained off-line. Therefore, the position recognition algorithm is lightweight and real-time.

5. Integration of Multi-Node Detection

Records from SNs should be integrated in AP to calculate traffic flow, especially when more than one SNs capture vehicle signals at the same time. First, time matching is implemented to find if there are any records reported almost simultaneously. Then, fusion algorithm extracts position information from these records and gets the actual vehicle number by an encoding mechanism.

5.1 Time matching

According to the record time of vehicle arrival and departure, two records from adjacent SNs are regarded as matching in time when following condition is satisfied:

$$\frac{L_{AB}}{\min(L_A, L_B)} \geq TH_{AB} \tag{3}$$

where L_A and L_B are vehicle signal durations on the two SNs respectively, and L_{AB} is the overlapping duration of two SNs, TH_{AB} is the matching degree threshold. Checking the records information of SNs one by one in sequence, all the matched records on adjacent SNs are found out for further processing.

5.2 Encoding and fusion

For ease of fusion, when a vehicle travels over the SN, the node is marked with 1, otherwise, it is marked with -1. Position marks are extracted from matched records, and these mark bits compose position code in the order of SNs layout. Regardless of the number of lanes, M is used to represent the number of vehicles travelling side by side across nodes array. The cases of M≤2 are discussed to design the fusion algorithm.

First, detection radius of SN is tuned to about 0.5m by adjusting algorithm parameters. Consequently, a vehicle can be detected by 1~3 nodes simultaneously when travelling across nodes array. As Table.1 shown, three bits are used to enumerate all position codes generated by case M=1, when 0 is an invalid bit. Furthermore, these codes are summarized as five basic codes. Basic code 1 with only one valid bit may indicate a small car, and basic code 5 with three valid bits may indicate a large vehicle. What's important, these codes can uniquely represent one vehicle passing in actual.

In case M=2, two vehicles traveling side by side may be detected by 3~6 nodes simultaneously. The codes for M=2 must be the combination of two basic codes. As the situation shown in Fig.1, code (-1 1 -1) is acquired when the BUS travels over SN_2 and detected by SN_1 and SN_3 as well. Similarly, the CAR results in code (1 1) on SN_4 and SN_5. As the BUS and the CAR travel side by side, a combination code (-1 1 -1 1 1) is acquired. All the codes for M=2 can be enumerated when vehicles are of different size and travel across nodes array with variable positions.

TABLE I. POSITION CODES IN CASE M=1

	Position Code		Basic Code
1	(1 0 0) (0 1 0) (0 0 1)	→	(1)
2	(1 1 0) (0 1 1)	→	(1 1)
3	(-1 -1 0) (0 -1 -1)	→	(-1 -1)
4	(1 -1 0) (0 1 -1) (-1 1 0) (0 -1 1)	→	(1 -1) (-1 1)
5	(-1 1 -1)	→	(-1 1 -1)

The fusion aims to extract the number of basic codes in a complete position code. The position code consists of {-1, 1} is processed bit by bit. If current processed bit with previous several bits can't compose one of the five basic codes, it is indicated that one more vehicle is detected on the basis of current flow count. The fusion state machine in Fig.4 is designed to process the code so as to realize traffic flow counting.

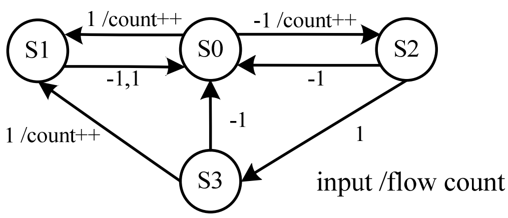

Fig.4 Code fusion state machine

The fusion state machine has four states:

S0: the first bit of next basic code is to be input;

S1: the {1} has been input;

S2: the {-1} has been input;

S3: the {-1 1} has been input.

Each state corresponds to different prefixes of basic codes. As the first bits of code are entered, the state machine starts with state S0, and the flow count is incremented while state changing. Through exhaustive enumeration and state machine processing, it's verified that all codes for case M≤2 can be resolved correctly.

Under none-fusion methods a trans-lane vehicle may be detected by two lanes, which is confused with two vehicles travelling side by side. Within MLVD, the confusing situations can be distinguished by encoding and fusion.

5.3 Applicability to multi-lane

There are usually 1~4 lanes for unidirectional road. For general traffic the horizontal safety distance between vehicles is considered, so the value of M is regarded not to exceed the number of lanes N. The applicability of MLVD to 3 or 4 lanes is investigated as follows.

For sceneries with 3 or 4 lanes, if M=N, then the travelling vehicles are intensive horizontally; considering the driving safety, each vehicle should travel over the SN in the middle of each lane. Above situation in four-lane scenery is given in Fig.5(a), and the position code can be expressed as (1 φ 1 φ 1 φ 1). The mark φ reported by SNs between every two lanes has the value of 1 or -1. Through enumeration, all valid codes will be resolved correctly by the designed state machine.

In four-lane sceneries, the situations of M=3 are discussed. In general, trans-lane driving happens when two free lanes are available. When there is one trans-lane vehicle of the three, the position code can be expressed as (1 φ 1 φ α β γ) as Fig.5(b) shown. The mark α must be -1, and β has the value of 1 or -1, γ is -1 or invalid. It is proved all codes will be resolved correctly by enumeration. Though the situations with two or three trans-lane vehicles are not common, most of the enumerated codes can also be resolved correctly.

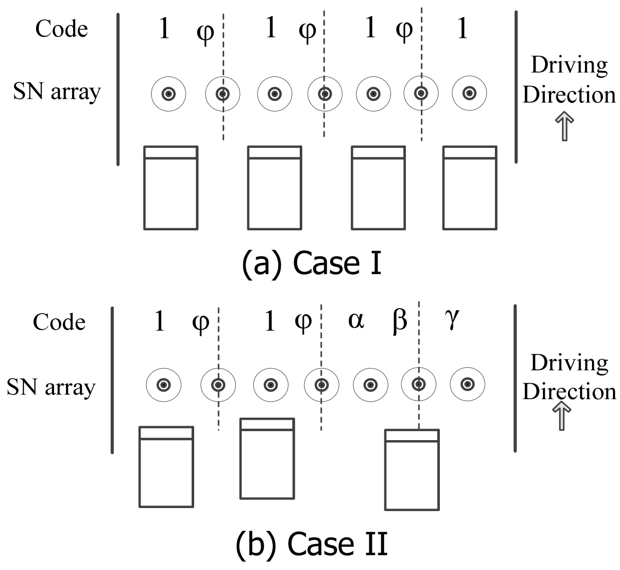

Fig.5 Typical code generated in four-lane scenery

According to the analysis above, MLVD method is applicable to sceneries of no more than four lanes. Meanwhile the software and hardware are compatible for nodes, the method can be easily expanded to accommodate different number of lanes. In addition, for motor way without isolation barrier at roadside, an extra SN can be deployed there to avoid missing vehicles.

6. Experimental Results and Analysis

SNs are implemented to acquire magnetic signal data on road. SN consists of main modules such as MSP430 microcontroller and HMC5883L magneto-resistive sensor. The sample rate is set to be 100Hz, and the acquisition data is exported to PC. The proposed method is verified in Matlab via data acquisition and off-line algorithm simulation.

6.1 Single-lane detection experiment

Datasets are collected from the SN placed in the middle of single lane. Dataset DS1 is collected on urban road with medium dense traffic, which lasts about 10min. DS2 is collected in the traffic congestion on urban road, which lasts about 40min. And DS3 is collected on the toll-gate lane with extremely slow traffic.

Test results of the three datasets are shown in Table2-4. To compare the performance of different methods, the datasets are processed by another two methods as well. The method in [7] is based on z component, and the method in [8] is based on the difference of total magnetic magnitude.

According to the results, all the algorithms achieve high accuracy (>95%) for medium dense traffic as shown in Table 2. The method in [7] and method in [8] are prone to recognize one slow vehicle as several vehicles, both of them cause many false positives detections as shown in Table 3 and Table 4. The method in [8] causes more false negative detections, for it's also prone to mix several close vehicles into one. SNVD performs better than other algorithms significantly for congestion and slow traffic. It's concluded that SNVD has excellent adaptability to different traffic density and velocity. Taking account of the total false detections for three datasets, the overall accuracy rate of proposed SNVD is 97.5%, while the methods in [7] and [8] achieve the same overall accuracy of 92.0%.

TABLE II. SINGLE-LANE DETECTION RESULTS FOR DS1WITH MEDIUM DENSE TRAFFIC

Type	Actual Flow	Detected Flow	False Negative	False Positive	Detection Accuracy
SNVD	125	126	0	1	99.2%
Ref[7]	125	130	0	5	96.0%
Ref[8]	125	128	0	3	97.6%

TABLE III. SINGLE-LANE DETECTION RESULTS FOR DS2 WITH CONGESTION TRAFFIC

Type	Actual Flow	Detected Flow	False Negative	False Positive	Detection Accuracy
SNVD	114	117	1	4	95.6%
Ref[7]	114	124	0	10	91.2%
Ref[8]	114	117	4	7	90.4%

TABLE IV. SINGLE-LANE DETECTION RESULTS FOR DS3 WITH EXTREMELY SLOW TRAFFIC

Type	Actual Flow	Detected Flow	False Negative	False Positive	Detection Accuracy
SNVD	37	38	0	1	97.3%
Ref[7]	37	44	0	7	81.1%
Ref[8]	37	49	0	8	78.4%

6.2 Multi-lane detection experiment

On the surface of urban road, three SNs are placed in a line with 1.8m distance between every two nodes, and SN_B is on the boundary line of two lanes. According to video record, 219 vehicles passed in 20min of the on-road data acquisition, which includes trans-lane vehicles as well as vehicles travelling side by side.

To evaluate the performance of MLVD method, several single-node detection algorithms without fusion are chosen as benchmark. These algorithms process the same acquisition data. Table.5 shows the results of experiment.

TABLE V. MULTI-LANE EXPERIMENT RESULTS OF DIFFERENT METHODS

Type	Fusion	Actual Flow	Detected Flow	SN_A Flow	SN_B Flow	SN_C Flow	False Negative [1]	False Positive I [2]	False Positive II [3]	Detection Accuracy
MLVD	Yes	219	218	85	140	102	1	0	0	99.6%
SNVD	No	219	187	85	X	102	34	0	2	83.6%
Ref[7]	No	219	181	79	X	102	40	2	0	80.8%
Ref[8]	No	219	186	84	X	102	37	1	3	81.3%

1. False Negative: missed on single sensor node
2. False Positive I: redundant detection on single sensor node
3. False Positive II: caused when calculating the total flow in AP

The detection accuracy of MLVD method with fusion is 99.6% as Table 5 shows, one vehicle causes false negative for it travels beyond the predefined two-lane boundary.

For none-fusion methods the false negative II is in the majority of false detection. That's because trans-lane vehicles are missed by SN_A and SN_C with small detection radius. In addition, trans-lane or adjacent-lane vehicles may be detected by SN_A and SN_C. Consequently, some of these vehicles cause false negative II in the none-fusion methods. Overall, the accuracy of MLVD outperforms by about 16.0%~18.3% than none-fusion methods.

Obviously, it's impossible to reduce false positive and false negative cases within none-fusion methods. MLVD method solves this problem via adding more SNs, reducing detection radius and an effective fusion mechanism. Due to constraints of field environment, experiment is conducted on two lanes. Nevertheless, position recognition and fusion algorithms are validated in experiments, and MLVD can be applied to more lanes for its compatibility and scalability as discussed in section 5.

7. Conclusion

In this paper, the single-lane vehicle detection method SNVD is proposed. SNVD is based on multiple features, with better performance against exiting algorithms for low velocity and dense traffic situations. Then, the method of MLVD is proposed to expand single-lane vehicle detection for multiple lanes. Based on SNVD, MLVD improves nodes layout and implements a fusion mechanism using vehicle position recognition. MLVD achieves an accuracy of 99.6% in experiment, solving the problem of trans-lane and adjacent-lane vehicles in multi-lane sceneries. It's concluded that MLVD has good adaptability to unidirectional multi-lane road.

Acknowledgments

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