Real-time Traffic Monitoring with Magnetic Sensor Networks

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Wireless Sensor Networks (WSN) provide an economical, convenient alternative solution to existing traffic monitoring systems, such as video recognition and inductive loops. However, there are many technical challenges in on-road real-time traffic information collection with WSN, e.g. accurate vehicle detection in low Signal-Noise-Ratio (SNR) conditions and reliable vehicle speed calculation. In this paper we propose a systematic solution to on-road real-time traffic monitoring with a magnetic sensor network. We propose a Similarity Based Vehicle Detection (SBVD) algorithm to detect vehicles in low SNR conditions by calculating the similarity between on-road signals and a referential signal. We propose a Collaborative Speed Calculation (CSC) mechanism to calculate vehicle speed reliably by redundant nodes and accurate reports of vehicle appearance. The CSC mechanism can calculate vehicle speeds accurately and trustworthy. We demonstrate through simulations and experiments that our proposed solution works effectively in noisy on-road environments. The vehicle detection rate is above 90% while no false alarm occurs and the error rate of speed calculation is under 10%.

Keywords: wireless sensor networks, traffic monitoring, magnetic sensor, vehicle detection, speed calculation

1. INTRODUCTION

Intelligent Traffic System (ITS) plays an important role in the modern transportation system. One hot field in ITS research is the development of traffic monitoring systems that watch over the traffic flow and collect traffic parameters on-the-spot. Only when the on-road parameters, such as vehicle volume and vehicle speeds, are correctly obtained, ITS is then possible to improve the public transportation effectively. Existing traffic monitoring systems are mainly based on video recognition or inductive loops. There are some shortcomings in these systems. Video-based systems can not work well in inclement weather conditions, like heavy rain or snow. Deployment and maintenance of inductive loops need to cut off the road surface and interrupt traffic vehicles. Moreover, both the two kinds of traffic monitoring systems are expensive and they are not suitable for large scale deployment.
Due to new characteristics, such as low-cost, deployment convenience and good scalability, WSN [1] offers an alternative to existing traffic monitoring systems. Compared to existing systems, WSN-based systems are much cheaper in cost and they can be deployed in large scale. Researchers believe that WSN-based traffic monitoring systems outperform existing solutions in both cost and deployment convenience.

Among all the vehicle detection methods, magnetic detection is a frequently used one, for the reason that magnetic detection of vehicle is relatively insensitive to deployment environments, e.g. poor weather conditions. A typical magnetic response of the passing of a vehicle is illustrated in Fig. 1.

![Fig. 1. Vehicle magnetic response in 3 axes (Z vertical, X-Y horizontal).](image)

To apply magnetic WSN in traffic monitoring, two problems should be solved. The first problem is to accurately detect vehicles on road. The second problem is to obtain more vehicle information, like vehicle speeds. Because of the cluttered environments, magnetic signal which is utilized to obtain vehicle information is always severely influenced by noise. Correspondingly, the Signal-Noise-Ratio (SNR) is low and algorithms which detect vehicles and calculate vehicle speeds should lessen the impact of low SNR. At present, there are still some technical challenges in solving the aforementioned two problems.

Several solutions [2-11] have already been proposed to solve problems in vehicle detection by WSN.

One of the vehicle detection methods is to distinguish a vehicle from collected signal with a fixed threshold. Based on the typical response of a vehicle, an idea is inspired to detect vehicles by a single threshold from the raw signal sampled by magnetic sensors [2, 3]. As the on-road environment is full of heavy noise, the choice of a single threshold often leads to a high false alarm rate and a low detection rate. To lessen impact of noise, Finite Input Response (FIR) filter is applied to smooth raw signal [5, 6]. A FIR filter is proposed to smooth the raw signal first [5], then a threshold is used to discern vehicle from the smoothed signal. However, our simulation indicates that adoption of a FIR filter can not deal with low SNR signal well.
Another vehicle detection method is to distinguish a vehicle with an adaptive threshold. Extra algorithm [4] is introduced to adjust the threshold dynamically because the authors found that the output of sensor’s ADC will change when the environmental conditions change first. A constant false alarm (CFAR) detector is applied to improve the detection performance [6]. However, accurate modeling and description of the noise in on-road environments should be known first and it is difficult to obtain them.

Vehicle speeds calculation [2, 10, 12] has been explored in WSN research. Several solutions are proposed to calculate vehicle parameters including vehicle speeds. Single node speed calculation is proposed [10], but it works in the hypothesis that the distribution of vehicle length is known. Speed calculation by inter-node cooperation [2, 12, 13] is also explored. The basic idea of these solutions is to calculate the interval between the time instants that a vehicle passes two sensor nodes. In [2], sensor nodes calculate vehicle speed according to the magnetic response waveform in Z-axis by a threshold based algorithm. As we mentioned, this solution is susceptible to low SNR. In [12], the solution also adopts a threshold based algorithm but an extra parameter $\delta$ is used to avoid false alarm to improve system performance. However, as described in [12], $\delta$ must be inversely adaptable to the speed. Furthermore, the choice of $\delta$ finally depends on a vehicle signature database which is difficult to build up. In [13], the proposed solution calculates the time interval by two nodes and uses an extra node to fuse the information. But low communication quality is not taken into account. Any communication failure will lead to the failure of speed calculation. All solutions mentioned above have not taken low SNR into consideration and the accuracy for interval calculation is not well solved. So the accuracy of vehicle speeds can not be assured. Furthermore, there is no redundancy in the aforementioned solutions, any node malfunction or radio communication failure will result in failure of speed calculation.

To solve the traffic monitoring problems in on-road environments, we develop a system named EasiTM. In EasiTM, a Similarity Based Vehicle Detection (SBVD) algorithm is proposed to detect vehicles and a Collaborative Speed Calculation (CSC) mechanism is proposed to calculate vehicle speeds. EasiTM works well when SNR is low. Deployment of EasiTM is also convenient. The accuracy of vehicle detection and speed calculation is verified in our simulations and experiments.

The rest parts are organized as follows: in section 2 we describe the algorithm in EasiTM, including a vehicle detection algorithm and a speed calculation mechanism. In section 3 we demonstrate our simulation and experiment results, also our analysis are presented. In section 4 we introduce our conclusion and future work.

2. ALGORITHMS IN EASITM

In EasiTM, the SBVD algorithm detects vehicle based on similarity between on-road signal and referential signal. A CSC mechanism is proposed to calculate vehicle speed according to the time interval which vehicle passes a fixed distance.

2.1 Similarity Based Vehicle Detection (SBVD) Algorithm

When a large ferrous object passes a sensor node nearby, the earth magnetic field will be distorted. Ideas are inspired to detect vehicles presence with magnetic sensors [2-4].
Fig. 2 shows a strong waveform and a weak waveform sampled in the direction of X-axis when a vehicle passes a sensor node. Theoretically, we can just detect the strong waveform from the original magnetic signal, like the threshold-related idea adopted in [2-4]. However, as Fig. 2 (b) displayed, the ubiquitous background noise may eclipse the weak change caused by ferrous objects. In this low SNR condition, it is difficult for threshold-related algorithms to achieve a high detection rate. Furthermore, the overlapping effect on earth magnetic change will occur if more than one ferrous object passes by the sensor node nearly at the same time. Fig. 3 shows an overlapped response caused by two vehicles which pass the observation point sequentially in a very short interval. Consequently, based on processing only the original earth magnetic signal, a high vehicle detection rate can not be gained by the aforementioned threshold-related methods.

We solve the vehicle detection problem from another perspective. By analyzing mass of vehicle magnetic data, we find that most waveforms are similar to each other. So we adopt the assumption that there is a referential waveform which is similar to the majority of actual vehicle responses. Then the detection task can be simplified by calculating the similarity between the response waveform and the referential waveform.

Suppose that the signal in Fig. 2 is denoted by \( m(t) \), \( t \) is the time variable. Then \( m(t) \) can be expressed as:

\[
m(t) = s(t) + n(t)
\]

where \( s(t) \) is the ideal response caused by a vehicle. \( n(t) \) is the background noise, it is commonly supposed to be random variable. Evidently, \( s(t) \) is zero when there is no vehicle. Suppose that \( h(t) \) is the referential vehicle response signal and ‘∗’ operation calculates the similarity between its operands, then we can express similarity between \( m(t) \) and \( h(t) \) by the following equation:

\[
m(t) \ast h(t) = (s(t) + n(t)) \ast h(t) = s(t) \ast h(t) + n(t) \ast h(t).
\]
In Eq. (2), we adopt cross-correlation [14] coefficient \( \rho \) as \('\ast'\) operation to calculate similarity:

\[
\rho_{fg}(n) = \frac{\sum_{m=-\infty}^{\infty} f(m)g(m+n)}{\sqrt{\left( \sum_{m=-\infty}^{\infty} f^2(m) \right) \left( \sum_{m=-\infty}^{\infty} g^2(m+n) \right)}}.
\]  

(3)

In Eq. (3), \( f \) is a discrete signal sequence of time variable \( t \), \( g \) is a known referential signal sequence which lasts a known time duration \( N \). DC component of \( f \) and \( g \) are supposed to be 0. Actually, in Eq. (3), the inner product of \( f \) and \( g \) is calculated at each time interval. If \( g \) matches certain piece of \( f \) sequence, the value of \( \rho(f \ast g) \), which indicates the similarity, is maximized. Denominator in Eq. (3) is adopted for normalization. As there is almost no similarity between noise \( n(t) \) and referential signal \( h(t) \), similarity output \((s(t) + n(t)) \ast h(t)\) will be maximized when one part of \( s(t) \) matches \( h(t) \).

According to Eq. (2), to calculate the similarity measurement, the first step is to find the referential waveform \( h(t) \), which should be as similar as possible to most vehicle response waveforms. Mathematical methods, such as curve fitting, are adopted to analyze actual vehicle response signal. Then we choose gaussian function as the referential response waveform, which is showed in Fig. 4. It should be pointed out that, other waveforms, such as polynomial curve, can also be chosen as a referential waveform.

Based on aforementioned ideas, we propose a Similarity Based Vehicle Detection (SBVD) algorithm. Fig. 5 shows an original signal and the normalized SBVD similarity. According to Eq. (3), there is a linear phase shift between the input signal and SBVD output. So we move SBVD output left to synchronize original data and SBVD output in Fig. 5. We can see that there is a SBVD peak corresponding to the presence of vehicle in original magnetic signal.

When a low SNR signal is referred, noise will almost cover the vehicle signal. SBVD algorithm shows its advantage in dealing with this kind of tiny signal. Fig. 6 shows the result of processing a tiny signal and normal signal showed in Fig. 3 by SBVD algorithm. The original signal was sampled when two vehicles passed the sensor node in a very short
interval. From the figure we can see that the second vehicle only caused a tiny change of the earth magnetic field. It is difficult to detect both the two vehicles by commonly used algorithms, such as classical threshold based algorithm. With a proper threshold, it is simple to detect the two vehicles by distinguishing two obvious peaks of SBVD output.

2.2 Collaborative Speed Calculation (CSC) Mechanism

Vehicle speeds can be used to infer the road occupancy status, and furthermore optimized traffic policies can be adopted to improve transportation efficiency. Therefore, vehicle speeds is a fundamental parameter which should be provided by Traffic Monitoring System.

The basic idea of speed calculation is to calculate the time duration $\Delta T$ in which vehicle passes a fixed distance. To calculate $\Delta T$, 2-node model [2, 12, 13] was commonly adopted. However, we argue that 2-node model is not reliable because node malfunction and communication failure, which can not be avoided in traffic monitoring, will result in calculation failure. So we adopt a 4-node cell in our system to cope with single node malfunction or communication failure by redundant sensor nodes. Fig. 7 shows the sensor nodes deployment of our multi-node speed calculation.
In speed calculation, the first problem is time synchronization of sensor nodes. We adopted a common way, master-slave synchronization. One sensor will broadcast its stamp and rest sensors will update its time stamp. Due to the difference of oscillators, clock drift will lead to asynchronization. Our experiments indicate that in ten minutes, the difference between two sensor nodes is within 60ms, which we consider an acceptable error in speed calculation, so synchronization is triggered every ten minutes.

To calculate vehicle speeds by multi-node accurately and reliably, another two problems should be solved. One problem is the collaborative mechanism of processing messages reported by different nodes, because that the speed is calculated in a cooperative way. Due to ubiquitous background noise, it is difficult to accurately report vehicle appearance on time. So another problem is the accurate report of vehicle appearance time in each node. Here we propose a Collaborative Speed Calculation (CSC) mechanism, including a sliding window based appearance report algorithm and a multi-node clustering mechanism, to calculate the speed more accurately and trustworthy.

2.2.1 Accurate report of vehicle appearance time

Considering the original signal, we define appearance point as the point that marks the arrival of a vehicle in the waveform. The puzzle in reporting the appearance point is the identification of appearance point in the original signal. As can be seen from the original signal in Fig. 2, it is really difficult to determine the moment of vehicle arrival. Traditional threshold-related method will not work well on this problem. To accurately identify appearance point, we adopted sliding window. Sliding window has already been applied in track-while-scan radar detection theory. The probability of sliding window detection is the probability of achieving m successes out of n consecutive events. Fig. 8 shows the idea of sliding window. Input of n-times determination in the time window can be expressed by sequence:

\[(t_1, t_2, \ldots, t_n, t_{i+1}, \ldots, t_{i+n-2}, t_{i+n-1}, \ldots)\]

\(t_i\) is set default 0 and is assigned 1 if the sampled magnetic value in time interval \(i\) meets certain condition, in our case, is the event that the value is smaller than a given threshold. If the sum of \(t\) in time window (from \(t_i\) to \(t_{i+n-1}\)) is larger than a given valve \(m\) \((n > m)\), then the corresponding event is announced to be detected. The window will slide right one step if corresponding event is not detected. The aforementioned siding window is also called \(m/n\) logic.
Now we will estimate the performance of sliding window. Suppose that the probability of event happened in each time interval \( t_i \) is \( p \), which in our algorithm is the probability that sampled value is smaller than a given threshold.

Then we can calculate detection probability of sliding window according to Eq. (4):

\[
P_{\text{success}} = \binom{n}{m} p^m (1-p)^{n-m} + \binom{n+1}{m+1} p^{m+1} (1-p)^{n-m-1} + \ldots + \binom{n}{0} p^n (1-p)^0.
\]  

Fig. 9 indicates the relation between detection probability \( P_{\text{success}} \) and probability \( p \) under different \( m/n \) logic. It should be pointed out if window size \( n \) is too large, then the detection sensibility or precision will be decreased. On the other hand, if \( n \) is too small, such as 1 or 2, sliding window detection will degrade to single threshold detection (solid line in Fig. 9). So here we choose 3/5, 4/5, 2/4 and 3/4 logic to plot the curve. It is evident that when a vehicle enters a sensor’s probing range, value of \( p \) is much close to 1, while there is no vehicle appearing in a sensor’s probing range, value of \( p \) is much close to 0, the uncertainty occurs because of random noise. So we adopt an assumption that \( p > 0.8 \) when a vehicle appears and \( p < 0.2 \) when no vehicle appears. In Fig. 9, compared to single threshold detection, \( m/n \) logic detection can increase the detection rate in “vehicle appears” area and decrease the false alarm rate in “no vehicle” area. In EasiTM, we choose 3/5 logic.

2.2.2 Inter-node collaboration mechanism

In order to discuss inter-node speed calculation, we suppose that all the nodes are
placed in two parallel roadsides like Fig. 7. The measurements of vehicle appearance in each node are \( t_1, t_2, t_3, t_4 \). The response strength of vehicle is \( str_1, str_2, str_3, str_4 \). According to our system deployment showed in Fig. 6, the vehicle speed can be calculated twice:

\[
v_a = \frac{d}{\Delta t_a}, \quad v_b = \frac{d}{\Delta t_b},
\]

Here,

\[
\Delta t_a = t_3 - t_1, \quad \Delta t_b = t_4 - t_2.
\]

Then we can calculate the speed,

\[
v = \alpha \cdot v_a + (1 - \alpha) \cdot v_b.
\]

(5)

It should be noted that the response strength is in direct proportion to SNR and more accurate result will be achieved if SNR is higher. So here in Eq. (5) we introduce weight coefficient \( \alpha \) to merge \( v_a \) and \( v_b \):

\[
\alpha = \frac{str_a}{str_a + str_b} = \frac{str_1 + str_3}{str_1 + str_2 + str_3 + str_4}.
\]

(6)

If any message of four sensor node was lost, e.g. Node1, \( v_a \) will be invalid. It should be noted that Eq. (5) will be invalid if any of \( v_a \) and \( v_b \) is invalid. In that case, \( v \) will be assigned the valid one. If both \( v_a \) and \( v_b \) are not available, which means at least two node message were lost, a calculation failure will be announced. However in our experiment we found that the case in which two or more messages were lost rarely occurred. By this mechanism, speed calculation will still be accomplished even if one node message is lost, so redundancy is implemented here.

3. EXPERIMENT AND VERIFICATION

Fig. 10 shows devices and scene of our experiment. We choose EZ210 [15, 16] as our sensor node hardware. Communication module of EZ210 node is CC1000. The sampling rate is set to be 100Hz. The distance between nodes was set to be 6 meters. Sink
node was put on the pavement, receiving messages from cluster head. Video camera was also put on the pavement to establish ground truth of experiment.

### 3.1 Estimation of the SBVD Algorithm

According to the result in section 2, the referential Gaussian signal $h(t)$ we used in the SBVD algorithm is as follows,

$$h(t) = -131.1 \times \exp(-(t + 0.02322)/0.4414)^2).$$

To evaluate the performance of the SBVD algorithm, we choose two kinds of algorithm as benchmark. Classical threshold algorithm and digital FIR filter based algorithm are compared in our simulation. We process same data obtained in our on-road experiments by these algorithms individually. All the algorithms are simulated twice with different threshold value.

#### Table 1. Original magnetic data for simulation.

<table>
<thead>
<tr>
<th>Type</th>
<th>Thr</th>
<th>Detected</th>
<th>False Alarm (FA)</th>
<th>Detection accuracy (%)</th>
<th>FA* rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBVD</td>
<td>Low</td>
<td>36</td>
<td>0</td>
<td>92.3</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>35</td>
<td>0</td>
<td>89.7</td>
<td>0</td>
</tr>
<tr>
<td>Classic Threshold</td>
<td>Low</td>
<td>37</td>
<td>32</td>
<td>94.9</td>
<td>82.1</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>25</td>
<td>14</td>
<td>64.1</td>
<td>35.9</td>
</tr>
<tr>
<td>FIR</td>
<td>Low</td>
<td>32</td>
<td>11</td>
<td>82.1</td>
<td>28.2</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>26</td>
<td>0</td>
<td>66.7</td>
<td>0</td>
</tr>
</tbody>
</table>

*Total = 39 (Real vehicle number by counting synchronized video); Detection accuracy = Detected/Total; FA rate = False alarm/Total.

Table 1 shows the result of our simulation. At first, by watching the synchronized video recorded when the simulation data was collected on-road, we counted 39 vehicles appeared in the video and we made it the total number of vehicles in the experimental data. In the “Detected” column, the data is the number of vehicles which is detected by the algorithms and a vehicle appeared in synchronized video in corresponding moment. In the “False alarm” column, the data is the number of vehicles which are announced by algorithms while no real vehicle appearing in the video in that moment. In SBVD simulation, the data is processed by the SBVD algorithm respectively with threshold 0.3 and 0.4. In classic threshold simulation, the data is processed by single threshold algorithm used in [2-4]. The value of threshold is 10 and 20 below the background noise strength. In FIR simulation, the data is first processed by a low pass filter, then a threshold is used to detect vehicle appearances. The cut-off frequency of filter is 4Hz. The threshold value used in FIR simulation is 3 and 15 below the background noise strength.

According to classic threshold simulation, the detection accuracy under low threshold is 94.8% while the false alarm rate is as high as 82%. Threshold is changed to optimize the false alarm rate to 64.1%, but the detection accuracy also decreases to 64.1%. We can see that although the threshold can be changed to achieve low false alarm rate, the detection rate will also decreases. So the choice of threshold in this kind of algorithm
is a contradiction.

In FIR simulation, the data is smoothed first. Although the SNR is improved and the detection accuracy is better than that of classic threshold, the contradiction in classic threshold simulation still exists.

Compared to the classical threshold and band-bass FIR simulation, the SBVD algorithm is not threshold sensitive. We can also see that the false alarm rate of the SBVD algorithm is 0 and the detection rate is nearly 90%. From this simulation we conclude that SBVD outperforms both classic threshold algorithm and FIR-threshold algorithm, not only because of its high detection rate, but also its low false alarm rate.

3.2 Verification of EasiTM and the CSC Mechanism

In this part we will first show the result of EasiTM and then verify the CSC mechanism. Ten groups of on-road experiments were conducted. The ground truth of vehicle number and vehicle speed are based on the digital video. The statistical results are listed in Table 2.

From Table 2 we can see that detection accuracy of EasiTM is above 90%. Missing detection occurred because of low communication quality. We choose group 1 in Table 2 to verify the CSC mechanism. The ground truth of vehicle speed was established by analyzing the digital video. As the FPS (frame-per-second) of our DV is 24, so the objective vehicle speed can be calculated according to the following equation:

\[ V_{ref} = \frac{L}{n / 24} \]

In Eq. (7), \( L \) is the distance between sensor nodes and \( n \) is the number of frames in which vehicle passes two nodes. Fig. 11 indicates the accuracy of speed estimation. According to data in Fig. 11, we can calculate that the average accuracy of speed estimation is over 90%. It can be seen form the figure that error rate of seventh vehicle is very large (actually higher than 20%), the reason was that one node’s report message was lost in radio communication. We can also conclude that two-node speed calculation is not reliable.

<table>
<thead>
<tr>
<th>Group</th>
<th>Total</th>
<th>Detected</th>
<th>Missed</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>9</td>
<td>1</td>
<td>90.00</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>16</td>
<td>15</td>
<td>1</td>
<td>93.75</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>4</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>5</td>
<td>5</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td>13</td>
<td>13</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>12</td>
<td>11</td>
<td>1</td>
<td>91.67</td>
</tr>
<tr>
<td>8</td>
<td>10</td>
<td>9</td>
<td>1</td>
<td>90.00</td>
</tr>
<tr>
<td>9</td>
<td>11</td>
<td>9</td>
<td>2</td>
<td>81.82</td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td>12</td>
<td>1</td>
<td>92.31</td>
</tr>
<tr>
<td>Total</td>
<td>104</td>
<td>97</td>
<td>7</td>
<td>93.27</td>
</tr>
</tbody>
</table>
4. CONCLUSION AND FUTURE WORK

In this paper we proposed a systematic solution, namely EasiTM, to solve traffic monitoring problems in the low SNR condition. The SBVD algorithm can effectively improve vehicle detection accuracy. By the CSC mechanism, we can calculate vehicle speeds with a low average error rate. As future work, the data fusion algorithm in clustering algorithm should be developed to gain more traffic information, such as vehicle direction, vehicle type and lane. We will also improve system robustness under low communication capacity.

REFERENCES

605-634.

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