Vehicle Ethernet Flow Estimation Using Intelligent Methods

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Abstract. For modern vehicle communications systems, it is vital to utilize advanced networks such as Ethernet to enhance the network speed, improve the service, and avoid the congestion. To this end, it is necessary to develop a hardware platform as well as a flow estimation scheme for system optimization. In this paper, we formulate the vehicle Ethernet platform using Duagon cards under the standard of IEC 61375. Then, we propose three intelligent methods for vehicle flow estimation, i.e., the support vector machine (SVM), the back propagation (BP) neural network, and recurrent neural network (RNN) using improved back-propagation through time (BPTT). Comparative studies are performed to validate the proposed scheme. The results provide technical support for statistical characters analysis and high speed monitoring of modern vehicles.

1. Introduction

Communication systems are vital to modern high speed railway vehicles, but they need improvement or optimization due to increasing demand of transfer speed and reliability [1]. Some experiment platforms have been developed, but most rely on personal computers or only use common softwares, so they can hardly been applied into real industrial applications.

In addition, for time series network flow of vehicle communication, flow estimation or prediction plays an important role for system monitoring. Rich results have been proposed such as autoregressive (AR) model, moving average (MA) Model, autoregressive moving average (ARMA), and auto regressive integrated moving average (ARIMA). Besides, machine learning algorithms have been adopted such as support vector machine (SVM), grey model (GM), and neural networks (NN) [2].

However, some network flow distributions are beyond traditional Gauss or Markov models. Meantime, SVMs require proper parameter tuning, while grey models can hardly tackle highly random data sets. Comparatively, neural networks are more preferable owing to the auto correlation of the vehicle flow and can be used for flow estimation [3].

In this work, we study the Ethernet network for high speed vehicle systems used in railway areas. After building up the industrial platform, we perform comparative studies for vehicle flow estimation. The key contributions of this paper are summarized as follows:

1) We use the Duagon cards to build up the industrial vehicle Ethernet platform. This platform meets the IEC 61375 standard [4-5], and can test multi-node communication, which is important to study the industrial Ethernet characters for high speed vehicles.
2) We propose three intelligent flow estimations methods, and perform comparative studies, which provide technical support for vehicle network monitoring.

The rest of the paper is organized as follows. First, the Ethernet platform is formulated using the Duagon cards and PCs. Then, the mathematical descriptions for the three intelligent algorithms are briefly provided. Next, the comparative simulations are performed to validate the estimation schemes. Finally, the concluding remarks are given.

2. Formulation of the Vehicle Ethernet Platform

Using the Duagon cards, we build up the vehicle Ethernet platform with the aid of PC equipments, as shown in Figure 1. The key modules are described as follows:

- **Sender**: One of the PCs acts as the sender module, which controls the Duagon Ethernet node to send the network data.
- **Receiver**: Another PC acts as the receiver module, which controls another Duagon Ethernet node to receive the network data.
- **Power supply**: The power supply module provides steady DC voltage in the range of 90V to 110V.
- **Duagon**: Two Duagon equipments are used as two Ethernet nodes, in which the I303 card is adopted as the key module.
- **Switch**: The switch is used to gather and distribute the common data for PC monitoring.
- **Wireshark**: The software is used to grasp the net data from the switch.
- **Network Debugger**: The PC is used to analyze and monitor the performance.

![Figure 1. Modules of the vehicle Ethernet platform](image)

The unique software used for Duagon card programming is Multiprog, which uses block functions for configuration and data transmission, as illustrated in Figure 2.

![Figure 2. Example of Multiprog software configuration](image)

With the above hardware and software platform, we can perform tests for varying scenarios, and gather experiments data sets for system performance analysis. To compare the data characteristics, we can compare the generated data with the open database of Ethernet network.

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3. Intelligent Algorithms Used for Vehicle Flow Estimation

In this section, we use three intelligent algorithms for vehicle flow estimation, i.e., the SVM, the BP neural network, and the improved BPTT network, with brief principle descriptions. Comparative simulations are performed to demonstrate the estimation results of the three methods.

3.1. SVM method

SVM has been widely used in states estimation owing to less sample demand and strong generalization ability. Note that the performance of SVM prediction depends highly on the kernel function and key parameters, so we need to take three aspects into account for vehicle flow estimation.

First, the proper kernel function should be set. Usually, this function is tuned by experience with considering the characters of data samples via experiments. In this work, we select the radial basis function as the kernel function. Second, the penalty factor should be set. That is, by tuning it, the generalization ability and divergence speed should be balanced. Third, the insensitive loss function should be determined. Proper value can ensure high performance of SVM prediction.

Note that SVM methods require less data samples compared to other network methods. On the other hand, large amount of data may bring heavier burden to SVM training. Thus SVM is suitable to some unique scenarios such as dual classification.

3.2. BP neural network method

BP neural network is a typical intelligent algorithm which adjusts the network parameters via back propagation. Generally, the gradient descent method is used for back propagation.

BP neural networks are trained with updating the network parameters to achieve the smallest loss function. They have shown superiorities in many application fields. However, in some special scenarios where the current information has some unique dependence relationship with historical information, the BP neural networks can hardly perform the estimation well.

3.3. Improved BPTT RNN

It is noted that vehicle network flow data show statistical and autocorrelation properties. Thus, it is preferable to adopt the RNN network with improved BPTT for estimation [6]. The expanded view of RNN neural unit is shown in Figure 3.

![Figure 3. Expanded view of RNN neural unit.](image)

Herein, $o$ is the output, $s$ denotes the intermediate state of the hidden layer, and $U$, $V$, $W$ are weighting factors. Then we have

$$a_k = \sum_{i=1}^l W_{ik} x_i + \sum_{h=1}^n W_{hk} b_h^{k-1}$$

(1)

where $a$ is the weighting factor mapping from the input layer to the hidden layer. The time series of the Ethernet flow are denoted as $SI = [SI_1, SI_2, SI_3, \ldots SI_n]$. Here we use the former 1000 samples for network training based on the BPTT. The specific parameters are described in Table 1.

| Parameter | Description |
|-----------|-------------|
| $\eta$    | Learning rate |
For the loop from $i = 1$ to $i = n_{ep}$ as well as $j = 1$ to $j = n_{ts}$, we perform the following steps:

**Step 1:** Compute the parameters as:

\[
\Delta W = E_1 \times \eta \times S(t) \\
\Delta TH_1 = E_1 \times \eta \times 1
\]

**Step 2:** Compute the hidden and input layer errors:

\[
E_2 = E_1 \times W \times (\frac{\partial S(t)}{\partial V}) \\
\Delta V = E_2 \times \eta \times S(t-1) \\
\Delta U = E_2 \times \eta \times I(t) \\
\Delta TH_2 = E_2 \times \eta \times 1 \\
E_3 = E_2
\]

**Step 3:** Perform BPTT to repeat the iteration loop as:

\[
E_3 = E_3 \times V \times (\frac{\partial S(t-k)}{\partial V}) \\
\Delta V = \Delta V + \eta \times E_3\times S(t-k-1) \\
\Delta U = \Delta U + E_3 \times \eta \times I(t-k) \\
\Delta TH_3 = \Delta TH_2 + E_3 \times \eta \times 1
\]

**Step 4:** Repeat the iteration form to $q = 1$ up to $q = W_{-}S$ as:

\[
S(q) = S(q+1)
\]

### 4. Comparative Simulations for Vehicle Flow Estimation Methods

#### 4.1. Data preparation

For flow estimation, we first perform data normalization as:

\[
x'(t) = \left( x(t) - x_{\text{min}} \right) / \left( x_{\text{max}} - x_{\text{min}} \right)
\]

After pre-process and abnormal detection, the data sets are divided into training data and test data. The training data are used to train the three intelligent models, and the test data are used to validate the performance of the methods. In this section, we adopt 1400 data for training and 208 data for testing.

#### 4.2. Comparative simulations

First, we use the SVM method for flow estimation. Here we tune the key parameters with trial and error. The penalty factor and loss function are tuned as $C = 4.6$ and $\varepsilon = 1.8$, respectively. Figure 4 shows the flow estimation results using the tuned SVM.

For BP-NN model, we tune and set the parameters as follows: the learning rate is 0.001, the iteration threshold is 4000, and the hidden layer neuron number is 8. The flow estimation results are shown in Figure 5.
The parameters of the improved BPTT RNN are set as follows: The unit numbers of input layer, hidden layer and output layer are set as 1, 25, and 1, respectively. The learning rate is 1 and network expansion time is 10. The flow estimation results are shown in Figure 6. The estimation errors of the three methods are shown in Figure 7.

Moreover, we list the quantitative analysis on the three methods, as listed in Table 2.

| Method     | $E_{RMSE}$ | $E_{MSE}$ |
|------------|------------|-----------|
| BP-NN      | 0.3506     | 0.1229    |
| SVM        | 0.1118     | 0.0125    |
| BPTT-RNN   | 0.0270     | 0.0007    |

It can been seen above that the RNN based on improved BPTT achieves the best estimation performance with smallest estimation error and smoothest curve.

5. Conclusion
In this work, the Duagon vehicle Ethernet platform is developed according to IEC 61375. Three intelligent methods are designed to estimation the Ethernet flow, that is, the SVM, BP NN, and RNN based on improved BPTT. Simulations are performed to validate the proposed scheme, demonstrating the superiorities of the improved BPTT-RNN, with the RMSE less than 0.03. This work may provide some technical support for future design of high-speed vehicle communication systems.
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