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Design of vehicle overload detection system based on geophone

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Abstract. A vehicle overload detection system is proposed based on geophone. Under normal circumstances, when overloaded vehicles and ordinary vehicles pass through the road, the amplitude of the ground vibration will be different, and the geophone sensor can detect tiny vibrations of the ground. The system includes information acquisition module, signal conditioning module and wireless transmission module. The collected vibration data is transmitted through the wireless transmission module to the background, and the SVM algorithm is used to classify the information and determine whether the vehicle is overloaded. Experiments show that the system can detect overload accurately.

1. Introduction

With the rapid development of current logistics industry, the question of transport vehicles overloading is becoming more and more serious. Overloaded vehicles will cause extensive damage to the road and huge economic losses to society, which seriously threaten traffic safety [1]. According to statistics, 70% of traffic accidents are caused by vehicles overloading. Therefore, the overloading of transport vehicles has become one of the crucial issues of traffic management.

In the field of overload detection, traditional static weighing system needs to intercept a part of vehicles from the normal traffic flow and weigh them in a static field [2], it takes a long time and affects the normal traffic. There are also many unsolved problems in the dynamic weighing technology, such as the small measuring speed range and the large system, which is inconvenient for installation and maintenance. This paper presents a non-intrusive dynamic overload detection method based on the basic observation that overloaded vehicles on the road will cause different vibration from normal vehicles. The proposed system can be used to detect the overload within a short time, and also can be used to make an early warning in the dynamic situation before forcing the suspected vehicles weighed statically by the road administration. At the same time, it has a small size, and the installation and maintenance are very convenient.

In this paper, vibration sensor is used to collect vibration data, according to the varied sizes of vibration data to detect overload. Raspberry pi is used as the core of data collection equipment. A signal conditioning circuit board is designed independently to filter and amplify original vibration signals, and convert analog signals to digital signals. The embedded nodes are connected by wireless network. Classic SVM model is used to classify the data and determine the vehicle status.

2. Overall Design and Proposed Embedded Node

2.1. System Architecture

As shown in figure 1, the whole detection system consists of detection nodes, transmission networks and the back-end servers. Detection nodes are used for sampling, the data is transmitted to the PC through a wireless router so that the waveform generated by ground vibration can be observed in real time. Data is stored in the database, and processed by the algorithm in the server. When the overload is detected, the server will send out a warning.

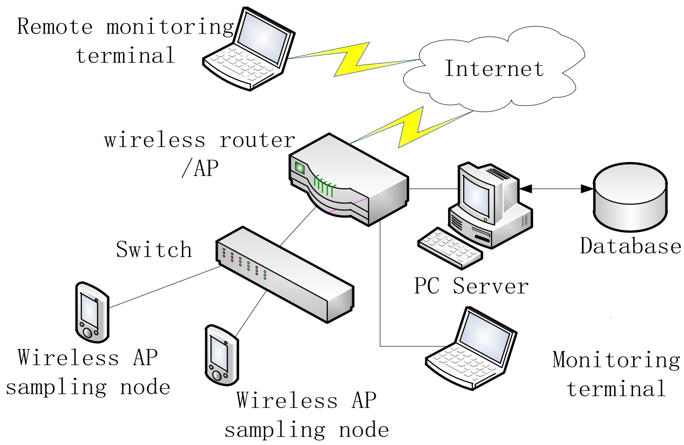

Figure 1. System Architecture

In order to meet the requirements of high precision and multiple nodes vibration data acquisition, the Wi-Fi wireless networking mode is used in system. EDUP EP-N8508GS is used as Wi-Fi module, which is a wireless AP with USB interfaces. In the case of a small range, star network with a single center can be used in wireless network, and all wireless sampling nodes are connected to the central switch. Between the slave computer and the host computer, TCP/IP protocol is used to ensure the reliability of data. In case of a wide range, due to the characteristics of Wi-Fi protocol, several wireless routers with WDS function [3] should be used.

2.2. Detection Node Design

Detection nodes need to be designed after the system design is completed, including selection of suitable control boards and sensors, as well as circuit design.

Since the USB Wi-Fi module provides the Linux driver, a control board with Linux environment is adopted. The raspberry pi is used in this paper, it has rich interfaces [4], which can well meet the need of development. The raspberry pi is connected with the USB Wi-Fi module, also connected with the vibration sensor through the signal conditioning board. The signal conditioning board sets aside SPI interface for raspberry pi. The read speed and time interval of SPI are adjusted through the SPI interface by raspberry pi, to control the sampling frequency.

In this paper, CDJ28HZ is selected as the geophone sensor to collect vibration data, it is mainly used for low frequency detection [5]. It has advantages that the output voltage signal is in proportional to the speed of the vibration signal, and the application field can be compatible with high frequency, intermediate frequency and low frequency; it has low output impedance, high signal-to-noise ratio. Therefore, it is very suitable to use geophone sensor to detect weak ground vibration. Feedback circuit is used to achieve the sensor's low-impedance output, coupled with A/D conversion circuit, the digital signal can be output. The A/D conversion circuit design is shown in figure 2.

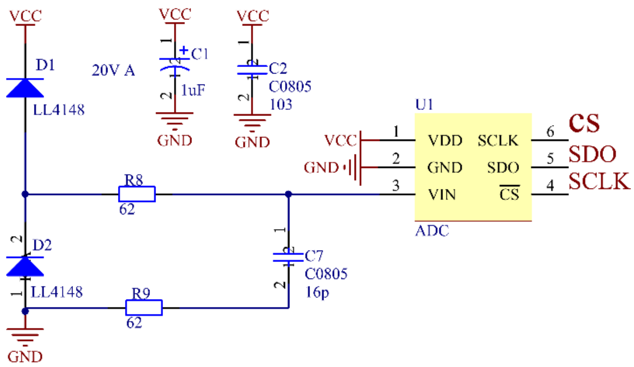

Figure 2. AD conversion circuit of CDJ28HZ

3. SVM Classification Algorithm

In order to distinguish overloaded vehicles from ordinary vehicles, classification algorithm is required. In the field of machine learning, classification algorithm requires that the system to analyze unknown pattern of input, in order to predict unknown categories.

3.1. Support Vector Machine(SVM)

The support vector machine is a two-class model, of which purpose is to find a hyper-plane to split the sample, and to separate positive and negative examples. Therefore the interval between positive and negative examples is the largest and classification results are more credible, and there would be better forecasting abilities for unknown new samples [6].

In the overload detection system, the sample is derived from the processed vibration data, the sample set is in format:$(x_1,y_1),\dots,(x_i,y_i), x \in R^n, y \in \{+1,-1\}$, x_i represent multidimensional feature vectors, and y_i represent classification markers with values of -1 and 1. -1 is used to show the normal situation while 1 is used for the vehicle overloading situation. The equations of the hyper-plane can be written as:

$$(\omega x) + b = 0, \omega \in R^n, b \in R$$

After being normalized:

$$y_i\big((\omega x_i) + b\big) \geq 1, i = 1,\dots,l$$

The classification interval is $\frac{2}{\|\omega\|}$. To maximize sorting interval, $\|\omega\|^2$should be minimized.

To optimize the above formula, the Lagrange theorem and KKT conditions are used for derivation, then the following form can be got:

$$Max \quad Q(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j d_i d_j x_i^T x_j$$

$$s.t. \quad \sum_{i=1}^{l} \alpha_i d_i = 0, \alpha_i \geq 0, i = 1,2,\dots,l$$

This is the famous QP problem, the decision plane equation is $\sum_{i=1}^{l} \alpha_i^* d_i x_i^T x + b^* = 0$ and α_i^* is the optimal solution to this problem.

Since there may be accidental errors while collecting data, the slack variable is used to optimize the problem [7]. Using ξ_i to represent the slack variable, the above problem is translated into the following optimization problem:

$$Min \quad \frac{1}{2}\omega^T \omega + C\sum_{i=1}^{l} \xi_i$$

$$s.t. \quad d_i(\omega^T x_i + b) \geq 1 - \xi_i \quad i = 1,2,\dots,l \quad \xi_i \geq 0 \quad i = 1,2,\dots,l$$

In the above formula, C is a penalty factor, which is a coefficient specified by user that represents the penalty for adding points to the wrong point. The objective function can be finally got:

$$Max \quad Q(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j d_i d_j x_i^T x_j$$

$$s.t. \quad \sum_{i=1}^{l} \alpha_i d_i = 0, 0 \le \alpha_i \le C, i = 1,2,\dots,l$$

To make the result of overload detection more accurately, the parameters in the classification model need to be adjusted. From the view of loss function, above problem can be understood as regularization term + loss term, and there is a C parameter to balance two parts. For the regularization term, there are L2-regularized and L1-regularized. With L2, the limitation of model space can be achieved, and over-fitting can be avoided. For loss term, hinge loss (for soft margin SVM) is commonly used, it can be subdivided into hinge loss (L1 loss) and squared hinge loss (L2 loss).

3.2. Algorithm Application

In the overload detection system, data obtained after being filtered is stored in the file in libSVM data format. The eigenvalues are separated by spaces in LibSVM data, +1 and -1 represent categories. In this system, the format is as bellow.

+1 1:71.8461538462 2:133.538461538 3:0 4:13.1538461538 5:44.1538461538

-1 1:0 2:0 3:0 4:0 5:0

The function of reading data: *y, x = svm_read_problem('data file location')*

The function of training model: *model = train (svm_problem, svm_parameter)*

The trained model is saved to the specified location. In following experiments, the model and the predict function can be used to predict experimental data.

4. System Testing and Analyzing

4.1. Experimental Testing

To identify differences between of overloaded vehicles and normal vehicles more intuitively, the wxPython module is used to construct the interface and display the vibration waveform in real time. After filtering, the contrast of vibration and vibration-free waveform is showed in figure 3.

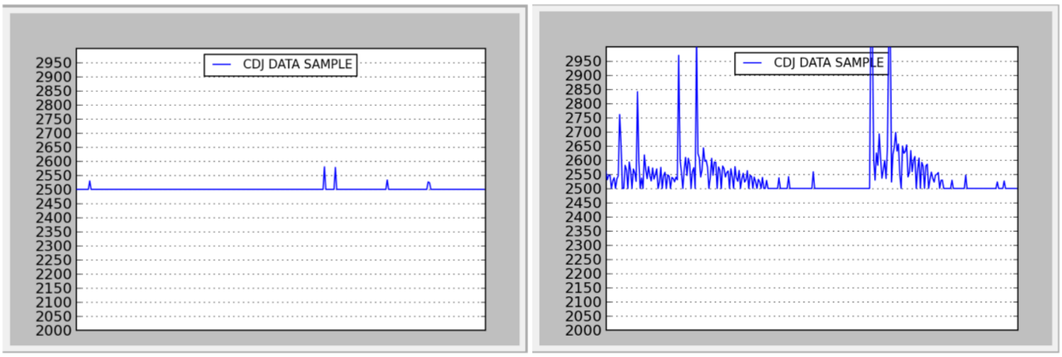

Figure 3. The contrast of vibration and vibration-free waveform

After filtering, it can be distinguished by naked eye that whether there is vibration or not. Then it can be determined that, after using SVM algorithm, the large vibration caused by overloading and normal vibration can also be very well classified. Field testing is carried out at a bus station. When there are no passengers and some passengers on the bus, the waveform contrast is showed in figure 4.

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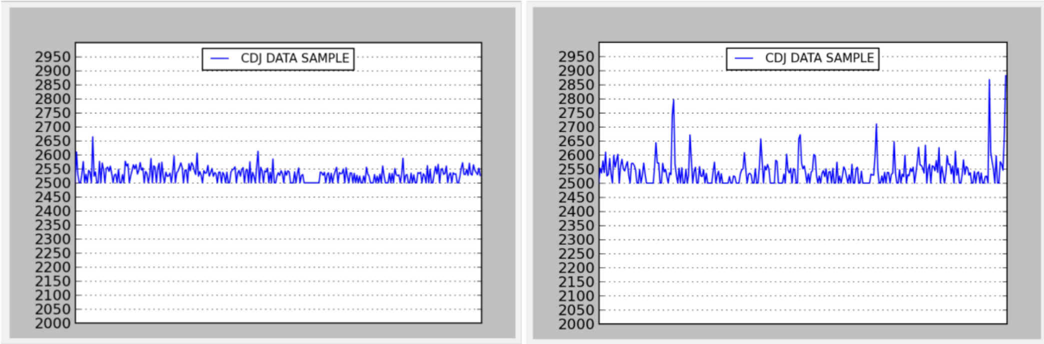

Figure 4. The waveform contrast between empty and crowded buses

The waveform comparison of the the full load and overload buses is showed in figure 5.

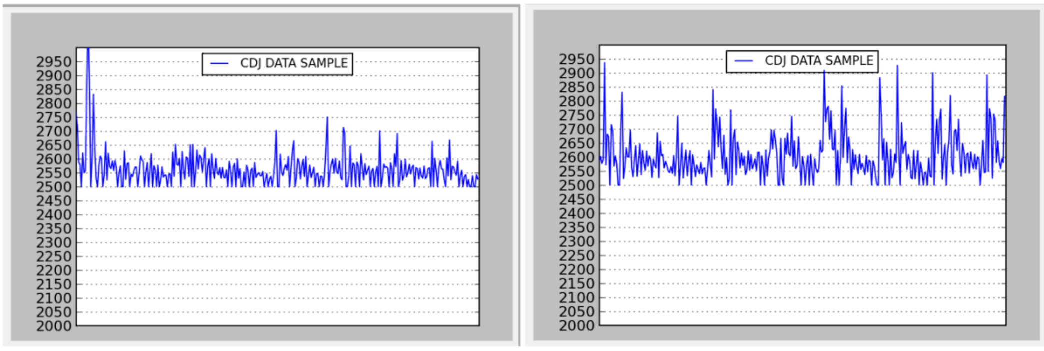

Figure 5. The waveform contrast between full-load and overload buses

4.2. Training Model Process and Application Result

This section focuses on adjusting of two important parameters--- loss type (-s) and cost (-c), to find the most appropriate parameters for prediction. Some data measured at the bus station are used as a training set, sample dimension is 5, and 156 samples are trained. Among two parameters, -s took 1(L2-regularized L2-loss support vector classification) and 3(L2-regularized L1-loss support vector classification), while -c rises from the minimum. The comparison is shown in the table below:

Table 1. Accuracy of training set when adjusting parameters

Value of s	Value of c	Accuracy	Value of s	Value of c	Accuracy
1	0.001	50	3	0.001	50
1	0.01	65.3846	3	0.01	52.5641
1	0.1	94.8718	3	0.1	82.0513
1	1	96.1538	3	1	95.5128
1	2	100	3	2	100
1	3	100	3	3	100

From the above table, with the increasing number of training iterations, the training set error decreases and finally converge. The training set and sample dimensions are relatively small, so it is easy to reach the convergence and when parameter C is set to 2 or more, the accuracy of the training set can reach 100%. In the same case, when the parameter s is set to 1, the accuracy is clearly higher. Therefore, in the final implementation, the parameter s is set to 1 and the parameter c is set to 2.

After being fully trained, the model is used in the actual detection. When an overloaded vehicle passes by, the output value of the model is 1 and the overload is detected. Due to the complexity in real traffic, false judgment may occur sometimes, and further improvement will be needed.

5. Conclusion
In this paper, based on the geophone sensor and SVM algorithm, a new type of vehicle overload detection system is established, which make it possible to detect the overloaded vehicle and transfer the relevant data to the background after the vibration signal is obtained. Then further processing can be done. The system has advantages of small size, high sensitivity, and it can adapt to different test environments. Relevant system tests showed that overloaded vehicles can be accurately detected by this system, which has a very good practical prospect.

6. Acknowledgments
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