A Study of BP Neural Network for Bus Unsafe Driving Behavior

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Abstract

Monitor for safe operation of the bus is one of the main content of the intelligent transportation system (ITS). Among them, the real-time safety monitoring for driving behavior is a hotspot of research in this field, based on the traditional monitoring means such as video, thermal infrared, there exist some problems, especially under the condition of insufficient light at night and the car crowded conditions effect is poor. In this paper based on driving behavior of active safety monitoring and early warning method, through the vehicle attitude sensor real-time acquisition vehicle running posture, suggesting driving behavior, when found unsafe for early warning, designed the corresponding BP neural network algorithm. The experiment result compared with the results of video footage, and the absolute value of error is less than 8%.

Keywords: unsafe driving events, BP neural network, MEMS, driving behavior, vehicle attitude

1. Introduction

The safety of the bus is always one of focus for the public and the government, which is also the important part of intelligent transportation system. In the past, mainly through to install the car recorder in the car, or install video monitoring equipment, however, these devices cannot implement active safety monitoring for buses. Vehicle traveling data recorder is mainly to keep a record of the equipment operation parameters and vehicle video monitoring equipment is mainly to video the vehicle condition. When the accident happens, those equipments can provide important clues for the accident, but now the active analysis of the clues do not enough, in other words, the research of the date mining based on the monitoring data is not enough.

QIN Hong-wu, SHI Cun-jie et put forward a kind of driving behavior and vehicle state monitoring system based on MEMS and GPS [1], and analyze the vehicle running status. Aiyan Lu et [2] studied the moving vehicle detection algorithm according to the tunnel monitoring video based on these characteristics parameters. Jiang Li, Yongjuan Li et analyze the unsafe driving behavior and its influencing factors [3], Santhosh krishna venkata [4] proposed an intelligent online vehicle tyre pressure monitoring system. Davide Curone and others give a study of real-time self-calibration algorithm for the person's attitude based on triaxial acceleration signal [5], Liming Wu, Likai Zhang et design a kind of artificial neural network algorithm for vehicle attitude with three-axis accelerometer [6]. All of these studies about monitoring the safety of the bus has very important implications, some research has made some substantial progress. This paper promotes scientific and reasonable unsafe driving events record system to improve the public transport safety management. Attitude measurement system is a kind of inertial navigation system. Traditional inertial navigation technology selects accelerometers and gyroscopes as its inertia devices [7-8], but gyroscope have disadvantages, such as poor impact resistance. So this paper uses MEMS-based tri-axial accelerometers MMA8452Q to collect the real acceleration data, uses neural network algorithm to analyze the data to get the unsafe driving bus events.

2. Attitude Estimation of the Bus
2.1. Build the Coordinate System on the Bus

In order to reflect the real attitude, this paper defines two coordinate system on the bus, which are navigation coordinate system OXYZ and carrier platform coordinate system O-xyz, as shown in Figure 1. The z-axis of the coordinate system OXYZ is parallel to the z-axis of the coordinate system O-xyz, they are both origin on the vehicle's centre of gravity. The coordinate system O-xyz is fixedly connected with the vehicle and changes while the vehicle attitude changes. The definition of car coordinates is presented in the middle of Figure 2: the origin point is car's center of gravity; X direction points to car's moving direction along the car's vertical axle, Y direction points to the car's right along its lateral axle; Z direction, X direction and Y direction construct a right-handed coordinate system. The two coordinate systems is consistent when the vehicle in a horizontal position.
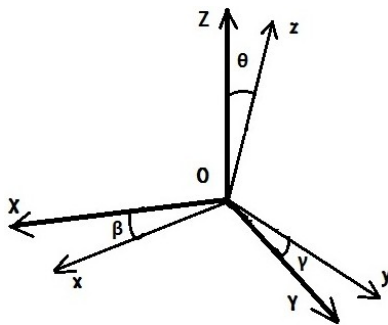

Figure 1. The Relationship of Carrier Navigation Coordinate System and Platform Coordinate System
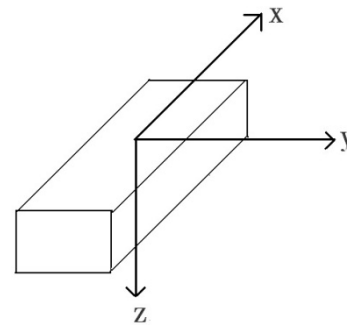

Figure 2 . The Definition of Car Coordinates

Attitude angles is defined as follows: θ is the included angle between carrier's vertical axle and the local horizontal, whose range is -90°~90°, we call it pitch angle; γ is the included angle between the carrier's lateral axle and local horizontal, whose range is -90°~90°as well, we call it roll angle; φ is the included angle between the projection of carrier's vertical axle and the earth magnetic field, we call it yaw angle. If we measure it in clockwise direction, the range of this angle is 0°~360°.

2.2. Calculate the Attitude of the Bus

In the case of the bus is stationary or moves uniform motion, the output data of the tri-axial accelerometer is acceleration of gravity in three axial component:

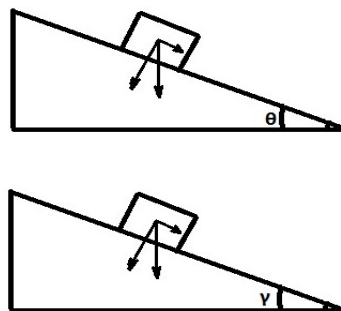$$[a_x, a_y, a_z] = [a_{gx}, a_{gy}, a_{gz}]$$

(1)

Figure 3. The Vehicle Attitude when it is Static

Assuming the x-axis is always coincident with the X-axis. When the bus parked on the road as shown in Figure 3, the output of the tri-axial accelerometer is as the following formula:

$$[a_x, a_y, a_z] = [g\sin\theta, 0, g\cos\theta] \tag{2}$$

$$[a_x, a_y, a_z] = [0, g\sin\gamma, g\cos\gamma] \tag{3}$$

So it is easy to get the pitch angle theta and the roll angle gamma with the tri-axial accelerometer's output data:

$$\theta = \arctan(a_x / a_z) \tag{4}$$

$$\gamma = \arctan(a_y / a_z) \tag{5}$$

Both of the above condition is the most common form of static body attitude. Assuming that C_n^b is transformation matrix form the coordinate system OXYZ to the coordinate system O-xyz :

$$C_n^b = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & \sin\gamma \\ 0 & -\sin\gamma & \cos\gamma \end{bmatrix} \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ 0 & 1 & 0 \\ -\sin\theta & 0 & \cos\theta \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 & \sin\theta \\ -\sin\theta\sin\gamma & \cos\gamma & \cos\theta\sin\gamma \\ -\sin\theta\cos\gamma & -\sin\gamma & \cos\theta\cos\gamma \end{bmatrix} \tag{6}$$

The output of the tri-axial accelerometer is the following formula:

$$[a_x \quad a_y \quad a_z]^T = C_n^b$$

$$= [g\sin\theta \quad g\cos\theta\sin\gamma \quad g\cos\theta\cos\gamma]^T \tag{7}$$

$$\theta = \arctan(a_x / \sqrt{a_y^2 + a_z^2}) \tag{8}$$

$$\gamma = \arctan(a_y / a_z) \tag{9}$$

2.3. Calculate the Parameters of the Bus Unsafe Driving Behavior

The unsafe attitude of the bus include: acceleration of the vehicle by the x-axis, which is mainly because the vehicle accelerates at the beginning, decelerate to stop, or suddenly decelerate caused by emergency. Acceleration of the vehicle by the y-axis is mainly due to the vehicle swerves. The acceleration of the vehicle along the z-axis is caused by the bumpy road. The actual motion of the vehicle may include the above three movements. These accelerations can make output vector of the tri-axial accelerometer deviate from the original direction of the gravity acceleration. Assuming G is the acceleration of gravity offset caused by the real vehicle acceleration, all the gravity offsets form a cone. So the key of vehicle attitude analysis is to eliminate the actual acceleration in each axis [9-10], but the acceleration in each axial direction is random, it is difficult to filter off with a specific algorithm. In order to reduce the complexity of the system, this paper uses the method of combining three tri-axial accelerometers to calculate the angular acceleration. The three tri-axial accelerometers are installed in the position as shown in the Figure 4, and the entire device is mounted in the center of mass of the vehicle. Assuming $\vec{a}_g = (a_{gx}, a_{gy}, a_{gz})$ is the acceleration of gravity. $\vec{a}_v = (a_{vx}, a_{vy}, a_{vz})$ is the actual acceleration, the output of the three tri-axial accelerometers are the following data:

$$\vec{a}_1 = (a_{1x}, a_{1y}, a_{1z}) = (a_{vx} + a_{gx}, a_{vy} + a_{gy}, a_{vz} + a_{gz})$$

$$\vec{a}_2 = (a_{2x}, a_{2y}, a_{2z}) = (a_{vx} - a_{gx}, -a_{vy} - a_{gy}, -a_{vz} - a_{gz})$$

$$\vec{a}_3 = (a_{3x}, a_{3y}, a_{3z}) = (-a_{vx} - a_{gx}, a_{vy} - a_{gy}, -a_{vz} - a_{gz})$$

Then we could get the following formula：

$$a_{gx} = \frac{1}{2}(a_{1x} - a_{2x}) \tag{10}$$

$$a_{gy} = \frac{1}{2}(a_{1y} - a_{3y}) \tag{11}$$

$$a_{gz} = \sqrt{g^2 - a_{gx}^2 - a_{gy}^2} \tag{12}$$

$$a_{vx} = \frac{1}{2}(a_{1x} + a_{2x}) \tag{13}$$

$$a_{vy} = \frac{1}{2}(a_{1y} + a_{3y}) \tag{14}$$

$$a_{vz} = a_{1z} - a_{gz} \tag{15}$$

$$\theta = \arctan(a_{gx} / \sqrt{a_{gy}^2 + a_{gz}^2}) \tag{16}$$

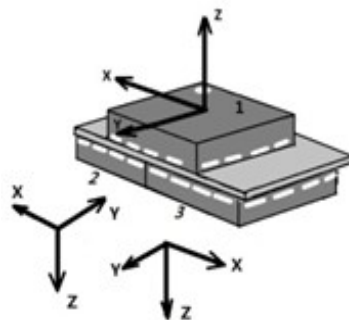$$\gamma = \arctan(a_{gy} / a_{gz}) \tag{17}$$

Figure 4. The Installation of Triaxial Accelerometers

3. Design of BP Neural Network for Bus Unsafe Attitude
Figure 5 shows a single neuron model of BP neural network, in general, at least one hidden layer before the output layer is needed. Three-layer network is selected as the architecture, because this kind of architecture can approximate any function with a few discontinuities [10]. The architecture with three layers is shown in Figure 6 below:
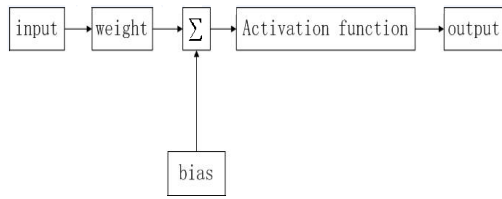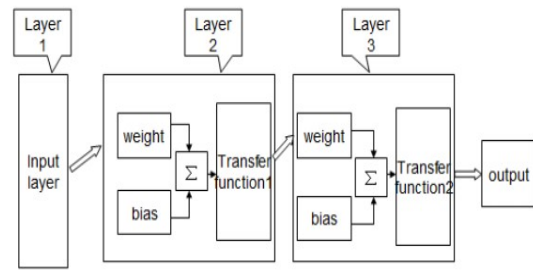
Figure 5. Neuron Model of BP Neural Network

Figure 6. Architecture of Three-layer BP Neural Network

3.1. The Input of BP Neural Network

As shown in Figure 7, it shows the core part of structural relationships of the neural network which is mapped the unsafe driving posture, and it adopt forward feedback BP network structure and input is X, as shows in the following formula :

$$X = [a_{vx}, a_{vy}, a_{vz}, \Delta a_{vx}, \Delta a_{vy}, \Delta a_{vz}, \theta, \gamma]$$

(18)

Among them, $\Delta a_{vx}, \Delta a_{vy}, \Delta a_{vz}$ are the state difference variables, they are difference between the present moment and the former moment, they are not only based on the current results, but also can get the current amount is determined by what state. This is done to reflect the vehicle movement model more close and build more precise mapping relationship.
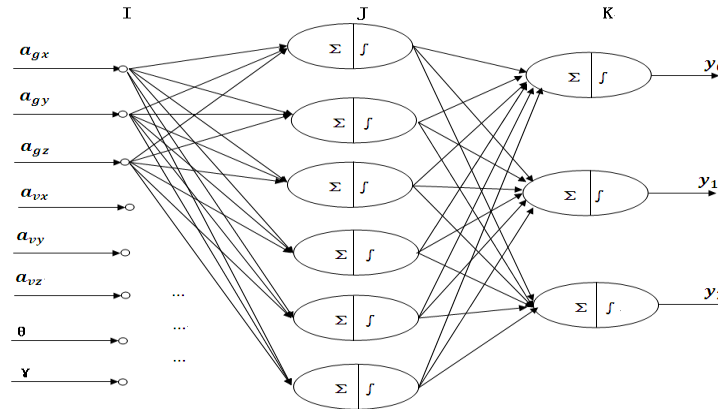

Figure 7. The Structure of BP Neural Network

3.2. The Output of BP Neural Network

Output targets are the real time vehicle attitude, which mean the demand presented at the same as input vectors changing. The output of BP neural network is Y, there are three output,

$$Y = [y_1, y_2, y_3]$$

(19)

The unsafe model as shown in Table 1. Because the incentive function is the sigmoid function, to avoid learning algorithm convergence, and improve the learning speed, the expected output are 0.99 and 0.01 instead of 1 and 0.

Table 1. The Output Model of BP Neural Network

model	Y	y_1	y_2	y_3
brake		0.99	0.01	0.01
accelerate		0.01	0.99	0.01
Sharp turn		0.01	0.01	0.99

3.3. The Hidden Layer of BP Neural Network

Toolbox in Matlab is used for training and simulating the BP network. The layout of the BP network consists of number of neurons and layers, connectivity of layers, activation functions, and error goal and so on [12]. It depends on the practical situation to set the framework and parameters of the network. The architecture of the network could be selected to achieve the optimized result. Matlab is one of the best simulation tools to provide visible windows.

According to Kolmogorov's theorem, a BP neural network with three layers is enough to complete any n to m dimensional mapping. And it is adequate to approximate arbitrary function, so this article uses only one hidden layer.

As for the amount of hidden layer node, under the condition of the input amount is not too large, the node is connected with the amount of the input and number of target classes. There, according to such characteristics of hidden layer structure, this paper takes empirical formula as a reference:

$$N_H = \frac{N_1 + (N_o, N_c)_{\max}}{2}$$

(20)

Among them, N_H, N_1, N_o, N_c are the amount of hidden layer node, the dimension of input vector, the node number of output layer and the number of target class. $(N_o, N_c)_{\max}$ is the maximum number of N_o and N_c. According to the formula (18), this paper chooses six hidden layer nodes.

3.4. Calculation of the Weight

Basically, there are three activation functions applied into BP neural network algorithm, namely, Log-Sigmoid, Tan-Sigmoid, and Linear Transfer Function. In order to simplify system, the neural network adopts the widely used Log-sigmoid function as the activation function.

$$y = f(x) = \frac{1}{(1 + e^{-x})}$$

(21)

According to the Delta's learning rule:

$$w(n + 1) = w(n) + \Delta w(n)$$

(22)

$$\Delta w(n) = \eta \delta(n) v(n)$$

(23)

$$v(n) = y(n)$$

(24)

$$\delta_k^K(n) = y(n)(1 - y(n))(d(n) - y(n))$$

(25)

$$\delta_j^J(n) = f'(u_j^J(n)) \sum_{k=1}^{3} \delta_k^K(n) w(n)$$

(26)

$$\delta_i^I(n) = f^{'}(u_i^I(n)) \sum_{j=1}^{8} \delta_j^J(n) w(n)$$

(27)

Among them, η is learning rate, $d(n)$ is expected output, $y(n)$ is actual output, n is number of iteration, K is the amount of output node, J is the amount of hidden node, I is the amount of input node, u is the input of the nerve cell.

The error energy of the output layer:

$$E = \frac{1}{2}(d(n) - y(n))^2$$

(28)

According to the desired output, the network trains the weight. The purpose is to adjust the connection weights to minimize the error energy of the output layer. The training process does not rely on prior knowledge and rules, and able to handle the data which is not trained. Thus has good adaptability and generalization ability.

4. Experimental Results

Three axis acceleration sensors MMA8452Q soldered to the board and attached to the body at the centroid as shown in Figure 8. Experimental data transmitted via wireless transmission module of GPRS to the host computer, data acquisition frequency is 100 times/sec. To extract the unsafe driving posture data, we through both manual recording and the camera records to take the unsafe vehicles traveling gesture data. Sample data obtained from the collection of driving posture data, and we can get the input data according to Equation (13) to Equation (17), respectively.

The neuralnetwork is trained by the obtained data (100 sets of training sample data was used), and obtained the individual neuron connection weights with relatively small error energy.

The linear neural network learning coefficient was set to 0.05, the objective function is 2×10^{-5}, and training steps set to 7000. Figure 8 is a diagram of BP neural network training, which shows that the algorithm has good convergence.

Each time experiments, made a total of five times were collected on the brakes, snap acceleration, turn left and right of these four unsafe driving behavior. In order to verify the validity of the algorithm and accuracy, in the process of real-time testing, also recorded the bus motion by a camera, compare the experimental results with the results of video, and the results as shown in Table 2.
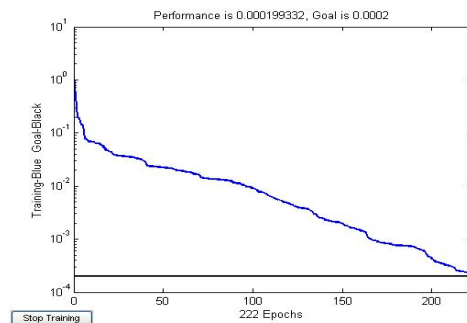

Figure 8. BP Network Training Figure

Table 2. The Experimental Results

	Video record (number)	The measured results (number)	absolute value of error
The brakes	98	96	2.08%
Urgent to accelerate	88	87	1.14%
Sharp left turn	65	60	8.33%
Sharp right turn	57	53	7.55%

5. Conclusion

This paper presents a sample method to discriminate the bus unsafe driving attitude real-timely with the recording data of the in-vehicle three-axis accelerometers, which is supported by the Shenzhen basic research project (the project's number is JCYJ20120617144302660, JC201006030851A). Firstly, we separate the gravitational acceleration data and the car actually acceleration data by placing the three-axis accelerometers sensors at different directions, and then through the learning and generation capability of the non-linear neural network we got the unsafe driving state model.

The accuracy of the algorithm was verified by the experimental results. And because the system is simple, low cost, so it has a certain practicality and also has great significance to traffic safety and driving comfort.

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