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Control the Vehicle Flow via GPS Monitor Center

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Abstract: - The purpose of this paper is to develop land vehicle navigation and traffic flow monitoring and a control system which is composed of Global Positioning System receivers and RF beacon communication. The GPS receivers and the other sensors detect the position, velocity, density, and flow rate of the vehicles on a freeway. By collecting these data and transmitting them to a monitor control station, called the center of dispatch, the vehicle traffic can be controlled and traffic congestion can be avoided. Two algorithms are developed for the GPS vehicle traffic flow controller which can estimate the velocity, density and traffic flow of the vehicles in order to ascertain whether the traffic is stable, critical stable or unstable. A backpropagation algorithm feedforward neural network approach is provided which has achieved high efficiency. The probabilistic decision base neural network approach selected to classify the stability of the traffic system got the some results as the feedforward neural network approach. An experiment showed that this system can solve traffic problems.

Key-Words: Global Positioning System (GPS), Feedforward Neural Network, Backpropagation Algorithm, Probabilistic Decision Base Neural Network (PDBNN).

1 Introduction

In the near future, as GPS receivers can be purchased at a low cost, more users will select them for navigation positioning. It is very convenient to install this equipment on a vehicle, and it not only obtains the position, velocity and heading of the vehicle, but can also be combined with an audio system and electronic mapping that can provide more information to accomplish driver-controlled navigation. The paper describes how the GPS receivers on the vehicles can obtain navigation messages and how these can be transmitted to a central dispatch by RF beacon. The monitor control dispatch center processes the data transmitted from each vehicle. The data contain the meteorological conditions, the presence of messages about accidents, matter pertaining to civil engineering works, and so on, and provide the users with real time information which can predict the time of arrival in order to avoid collision. The center of dispatch also estimates the density and traffic flow of the vehicles and ascertains whether the traffic is busy or not, to let the driver decide whether to take the freeway or not in order to avoid congestion on the freeway. The function of the whole system is shown in Figure 1.

A number of papers have been discussing related subjects. M. Papageorgion *et al*. described a neural network approach to freeway network traffic control speed [1]. L. Florio and L. Mussone setup neural network models for classification and forecasting freeway traffic flow stability [3]. M. G. Quinn presented a highway agency model for traffic management [4]. In addition, a number of papers explored air traffic management [2, 5~14]. None of these papers above, however, has discussed how to use GPS receivers to get relevant traffic data. In this paper, we in particular consider the use of GPS receivers to obtain navigation messages and send them to a central dispatch. The central dispatch combines these messages with other information, ascertains the level of stability of the traffic system, and predicts speed flow and the arrival time, to provide the user with a reference for making a decision whether to take the freeway or not.

This paper aims at setting up a real time kinematic GPS positioning and attitude determination algorithm using a single frequency L1 carrier phase double difference measurement equation, and the extended Kalman filter method to resolve the real-time positioning and the attitude of the navigator. Section 2 describes a theoretical derivation of KGPS positioning. Section 3 demonstrates how by using the attitude determination algorithm the attitude of navigator can be found. In Section 4, the extended Kalman filter approach is explained. Experimental results and discussion are described in Section 5. Section 6 presents some conclusions.

2 Message Collecting and System Description

First, the GPS navigation data, the vehicular position, velocity and heading / attitude, are collected. Then, the data related to the traffic conditions, messages about accidents, traffic obstacles, particularly busy traffic, highway management, signals light failure, and road work are obtained by a fix/moving sensor station. Finally, the messages about meteorological conditions like brightness, velocity, fog, rain or snow are obtained.

These three kinds of data are sent to the vehicle dispatch center by radio. An artificial neural network algorithm is used to estimate the flow, the speed and vehicle density and to ascertain whether the traffic is stable or not, and even to predict the time of arrival. The results are sent to the users in real time by radio for reference, to provide them with a criterion whether to increase or reduce speed or whether to take the freeway or not.

At present on Taiwan’s Freeway No.1 and No.2 the vehicular flow, the heavy load and the speed average data are collected every five minutes. From these we can easily obtain the vehicular flow, heavy load percentage and flow density data per hour. We think the dynamic model of traffic must have some relationship with the vehicular flow and density. But the relationship cannot be expressed by a concept formula or by a statistic linear approach. This paper attempts to set up a relationship with the artificial neural network. Figure 2 shows the backpropagation neural network model in which the flow vs. density and average speed vs. vehicle density relationships are set up in a new way.

If we know the relationship between the vehicle flow and the vehicle density, that can assist us in the analysis of vehicular stability. Figure 3 shows a relationship between vehicle flow and vehicle density. If the flow vs. density differential is positive, then the system is stable, which means that the system has the capacity to allow a rise in the vehicular flow. The system is critical stable if it is between the maximum and the 90 percent of the maximum of the flow-density curve. If the other parameters are fixed, then it can improve the density to input the backpropagation neural network, as shown in Figure 2. In this way, the flow-density curve can be obtained as shown in Figure 3, and it can be decided whether the system is stable, unstable or critical stable. When it is stable, the stability neural network output is 1. When it is unstable, the output is 0. When it is critical stable, the output is 0.5. Then we can get the stability neural network training and test data and input them as a density, flow and heavy load percentage. The output is 1 or 0 or 0.5. Figure 4 shows the backpropagation stability neural network model.

3 Estimate the Time of Arrival Algorithm

The users transmit some navigation data to the control center of dispatch. The data are including the vehicle of current position, velocity, and heading. The central dispatch has received these data, then processes them and estimates the time of arrival, determines the vehicle flow, density and velocity, then judges the system stability of the traffic flow. The time of arrival algorithm is to develop as follows.

Case 1. To discuss the traffic flow on the entrance of freeway as shown in Figure 5, if car A drives on the freeway with GPS receiver and RF beacon, car B just only installs RF beacon that drives to enter into the freeway at that time. Car A can be communicating with the center of dispatch each other including the navigation messages, but car B or another cars just can receive the warning signal which can predict the time of arrival to collide through the wireless radio frequency. Given car A and car B positions, velocity, heading, and the range of collision.

$$x_{t+\Delta t} = x_t + \Delta x = x_t + \frac{dx_t}{dt} \cdot \Delta t, \quad and \quad x_A - x_B = D,$$

$$D^2 + (\frac{dx_A}{dt} \cdot \Delta t)^2 - 2D(\frac{dx_A}{dt} \cdot \Delta t)\cos\theta_1 = (\frac{dx_B}{dt} \cdot \Delta t)^2 = L^2,$$

To solve Δt, then it can predict in how much speed to drive under this condition, passing Δt, it will collide. The center of dispatch should issue a warning message for car B or another cars.

Case 2. To discuss for any cross local way, car A and car B will crossover each other. They are installed the GPS receivers and RF beacon, can communicate with the center of dispatch. The car A and car B will transmit themselves navigation messages to the C.O.D., and receive the time of arrival and navigation data from the C.O.D. Given car A and car B positions, velocity, heading, and the range of collision,

$$D^2 + (\frac{dx_A}{dt} \cdot \Delta t)^2 - 2D(\frac{dx_A}{dt} \cdot \Delta t)\cos\theta_1 = (\frac{dx_B}{dt} \cdot \Delta t)^2,$$

$$D^2 + (\frac{dx_B}{dt} \cdot \Delta t)^2 - 2D(\frac{dx_B}{dt} \cdot \Delta t)\cos\theta_2 = (\frac{dx_A}{dt} \cdot \Delta t)^2,$$

To solve Δt, then it can predict the time of arrival Δt, and the position of collision x_C under this speed.

We can sample the data and list all the possible cases. Define the velocity of car B, $\frac{dx_B}{dt}$ equals to the symbol " V_i ". The constrain of velocity is $30km/hr \le V_i \le 90km/hr$, find the time of arrival Δt, if $\Delta t > t_{\max}$, then the C.O.D. should alarm a warning signal to the car B. Where the $t_{\max}$ consists of a transmission time between the car B and C.O.D. The propagation delay time on the circuit and the computer calculation time can express as

$$t_{\max} = 0.3 \times 2 + 0.1 + 0.3 = 1.0\,\text{sec}.$$

Refer to Figure 5, the time of arrival system is described.

4 Rebuilding the System Artificial Neural Network

This paper proposes two artificial neural network approaches to estimate traffic flow, density and stability on a freeway. Before explaining these two algorithms, we set up an environment database for a freeway as shown in Table 1 for the normal range of parameters. The system stability can be estimated with these two algorithms that is shown in Figure 6.

5 Backpropagation Neural Network Algorithm

The basic principle of backpropagation neural network is to use the gradient steepest descent method to reduce the error function to the minimum. It is the most popular model of expression of the artificial neural network. From the backpropagation neural network configuration, the input layer is used to accept the input signals, which are already expressed by multi-input vectors.

The middle layer is used to express the intersection impact of the input process unit, and the output layer is the output vector of the artificial neural network to be used to express the result of the operation. If the input layer accepts the input signal, then it adds weighting operation and transfer to the neural of the hiding layer. The neuron of the hiding layer sums all input weighting vectors and feedforward propagation to the output layer.

In this process, the error will be calculated, whether it is small or not, otherwise it will be back to adjust the weighting factor. It will go on calculating the error until the tolerance is small and convergent. The first layer output is (density, veh.%, flow) = (X_1, X_2, X_3). The second layer expresses

$$H_{2j} = f_2(\sum_{i=1}^{3} W_{2ij} \cdot X_i - \theta_{2j})$$

Where $f_2(Net) = \frac{e^{Net} - e^{-Net}}{e^{Net} + e^{-Net}}$. W_{2ij} is the weighting between the first layer i output and the second layer j neuron. θ_{2j} is a bias of the second layer j neuron. The third output is $H_{3j} = f_3(\sum_{i=1}^{8} W_{3ij} \cdot H_{2i} - \theta_{3j})$, where $f_3(Net) = \frac{1}{1+e^{-Net}}$. W_{3ij} is the weighting between the second layer i output and the third layer j neuron. θ_{3j} is a bias of the third layer j neuron.

The final output is

$$Y = f_4(\sum_{i=1}^{6} W_{4ij} \cdot H_{3i} - \theta_{4j})$$, where

$f_4(Net) = \frac{1}{1+e^{-Net}}$. W_{4ij} is a weighting between the third layer i output and the output layer j neuron. θ_{4j} is a bias of the output layer j neuron. The relationship from the input X to the output Y is

$$Y = f_4\{\sum_{l=1}^{6} W_{4kl} \cdot f_3[\sum_{j=1}^{8} W_{3jk} \cdot f_2(\sum_{i=1}^{3} W_{2ij} \cdot X_i - \theta_{2j}) - \theta_{3k}] - \theta_{4l}\}$$

This is a highly nonlinear relationship. Because the stability and the density-flow cannot use a linear formula or statistic mathematics to express both relations, we have selected the nonlinear characteristic of artificial neural network to set up this relationship. The weighting and the bias of (1) are used to the concept of the gradient steepest descent method to minimize an error function and to be obtained. If the function E is an error function, which is defined as

$$E = \frac{1}{2}\sum_{m=1}^{N}(Y_m - \hat{Y}_m)^2$$

where $\hat{Y}_m$ is the true output of network, then the weighting correction is

$$\Delta W_{ij} = -\eta \cdot \frac{\partial E}{\partial W_{ij}}$$

The bias correction is

$$\Delta\theta_j = -\eta \cdot \delta_j^n$$

The simulation and experiments are performed and it can be find a good result as shown in Figure 11.

6 Probabilistic Decision Base Neural Network Algorithm

S. Y. Kung *et al*. have developed this algorithm at Princeton University. Because of the use of the backpropagation neural network, there exists an unobvious classified intermediate area. If we use the probability neural network and classify the system into stable, critical stable and unstable, which is decided by the probability, then the unobvious area will be canceled. Below we intend to discuss how the probability neural network can be applied to the estimation of stability. The input layer is to express an input variable of the network, and its process number depends on problems. Here, we use three input variable (density, veh.%, flow) = (X_1 , X_2 , X_3), whose transfer function is a linear transfer function $f(x) = x$. The hiding layer is to express a training example, and each process unit expresses a training example. The hiding layer connects with the input layer is the characteristic vector of this training example. It is called the weighting matrix W_xh between the input layer and the hiding layer. It can express

$$W\_xh_{ih} = X_i^h$$

where X_i^h is the i input variable of the h training example. The output layer is used to express a classification. It connects with a process unit of the hiding layer that is the classified message of the training example. It is called weighting matrix W_hy between the hiding layer and the output layer.

$$W\_hy_{hj} = \begin{cases} 1 & if \quad T_j^h = 1 \\ 0 & if \quad T_j^h = 0 \end{cases}$$

where T_j^h is the j output variable of the h training example. If this variable is 1, it expresses that the example belongs to j type. If it is 0, it expresses that the example doesn't belong to j type. The output of input layer is (density, veh.%, flow) = (X_1, X_2, X_3). The output of hiding layer is $H_j = \exp\left[\frac{-\sum_{i=1}^{3}(X_i - W\_xh_{ij})^2}{2\sigma^2}\right]$

where σ is a smoothing parameter of network. W_xh_{ij} is the weighting between the input layer i input and the hiding layer j training example. The output of output layer is

$$Y_k = \frac{\sum_{j=1}^{n} W\_hy_{jk} \cdot H_j}{\sum_{j=1}^{n} W\_hy_{jk}}$$

where n is a number of the training example. W_hy_{jk} is the weighting between the hiding layer j training example and the output layer k output. The relationship between the input X and the output Y is

$$Y_k = \frac{\sum_{j=1}^{n} W\_hy_{jk} \cdot \exp\left[\frac{-\sum_{i=1}^{3}(X_i - W\_xh_{ij})^2}{2\sigma^2}\right]}{\sum_{j=1}^{n} W\_hy_{jk}}$$

The last classified result is the m type, where the domain of m is $\{m \mid Y_m = \max(Y_k) \quad k = 1, 2, 3\}$ and therefore the outcome probability of the m type is larger.

7 Experimental Results

For a period of time, we have observed the northbound and southbound traffic of Freeway No.2 and collected the traffic flow, vehicle velocity and density per five minutes data. All the data that we obtained are in the stable area, so it can be assumed that most vehicles moved in a stable condition, in other words, in that period the vehicles could be driven at a slower or higher speed, as shown in Figure 8. It cannot be seen the critical stable range in this Figure. If the traffic density is high, up to a busy condition, the vehicle velocity will slowly decrease, and then the traffic flow will automatically diminish.

Using the data that we collected from detectors, we proceeded to employ the backpropagation neural network method to train and obtain a flow-density function chart, shown in Figure 9. From this chart, we can see that the maximum of flow is about 4392 veh./hr, which determines the traffic stability of the freeway, as shown in Figure 10. Figure 11 shows the results when the backpropagation neural network simulation was used.

From Figure 11, we can see that a transition area of unobvious classified. So we have selected the probabilistic decision base neural network to perform classified. Through the simulation of probability neural network approach, the total number of the sample data is 1000, and that of the training samples is ten, as shown in Figure 12. If the total number of the sample data is 1000 and that of the training samples is 30, then Figure 13 shows this condition. We intend to collect more data including crowded traffic conditions, when vehicle density is high, and when it approaches to be completely clogged. We will use these data to analyze and justify whether the system is stable or not, and provide the data for reference.

Conclusions

This paper discussed the use of GPS receiver and other sensors to detect the vehicle position, speed, density and flow on the freeway, and then how a center of dispatch collects these data and processes them with the meteorological data and matters pertaining to civil engineering works on the road. Two artificial neural network algorithms are used to predict the vehicle velocity, density and traffic flow and to judge the stability of system. The preliminary experiments using the back-propagation feed-forward neural network to estimate a traffic flow, time of arrival and stability proved highly efficient. If one uses the probabilistic decision base neural network method to justify and classify the stability of the system, the results can be obtained more obvious then with the backpropagation approach.

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Table 1 Normal Range of the Parameters

Parameter	Minimum	Maximum
Vehicle Flow (veh./h)	0	5000
Vehicle Density (veh./km)	0	150
Vehicle Velocity (km/h)	0	150
Heavy Load Vehicle %	0	100
Visibility (m)	0	300
Meteorological	0(Clear)	1(Rain)
Brightness	0(Night)	1(Day)

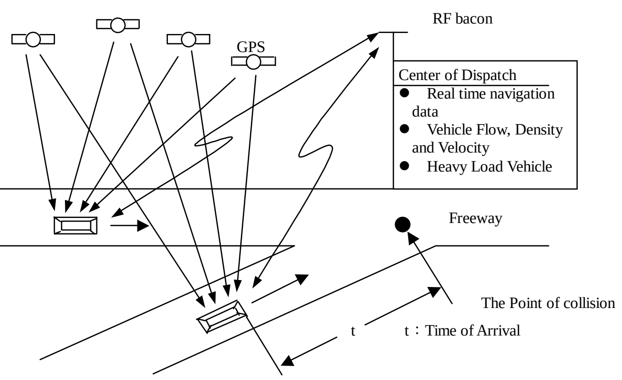

Fig. 1 GPS Vehicle Flow Control Functional Block Diagram

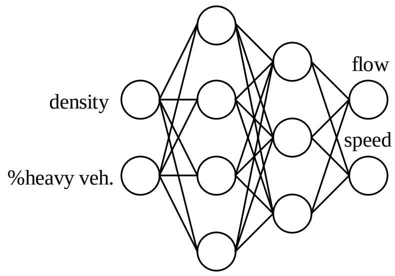

Fig. 2 Backpropagation Artificial Neural Network Model

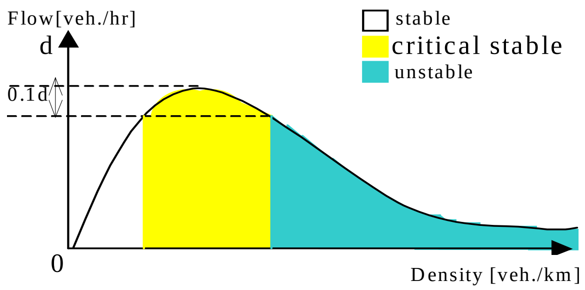

Fig. 3 Vehicle Flow-Density Relationship

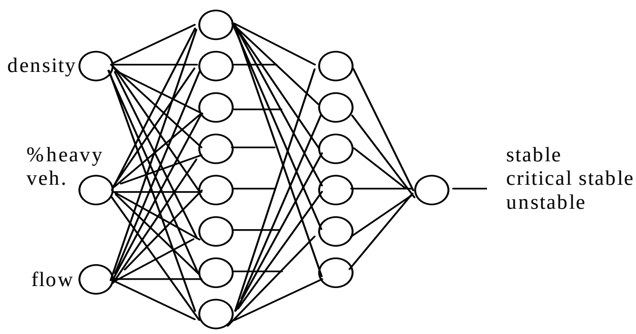

Fig. 4 Backpropagation Stability Neural Network Model

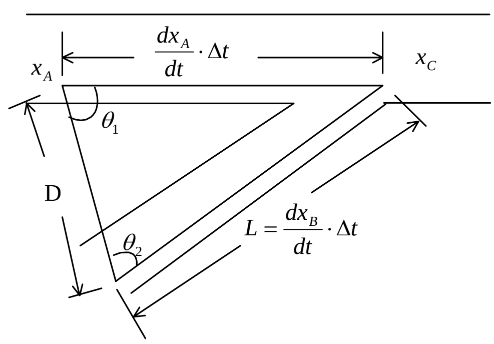

Fig. 5 Time of Arrival System Description

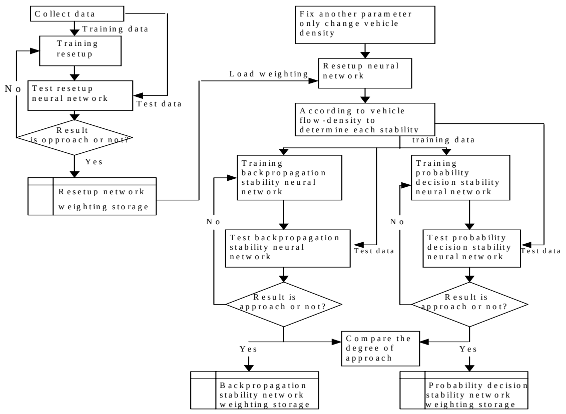

Fig 6 System Flow Chart

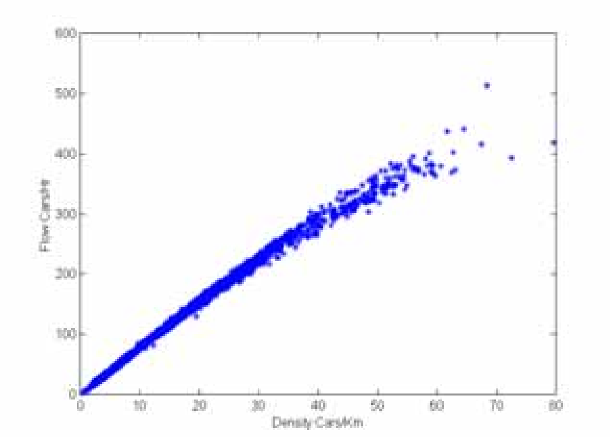

Fig. 7 Estimate the Stability Using Probability Neural Network

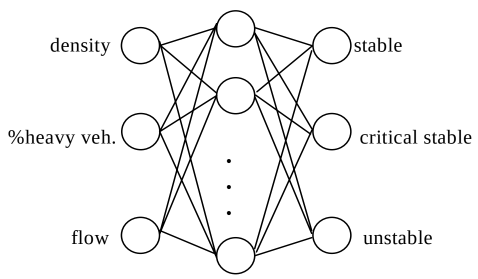

Fig. 8 Vehicle Flow-Density Analysis

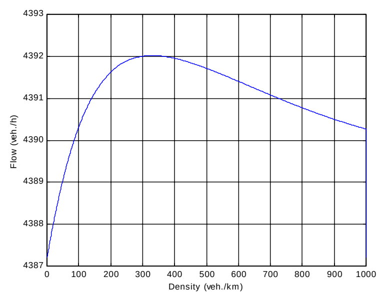

Fig. 9 Flow and Density Relationship

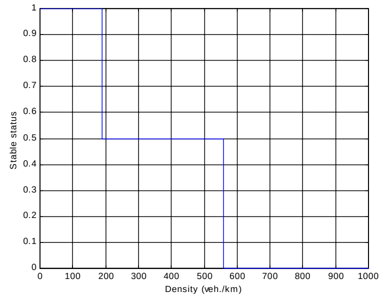

Fig. 10 Stability and Density Relationship

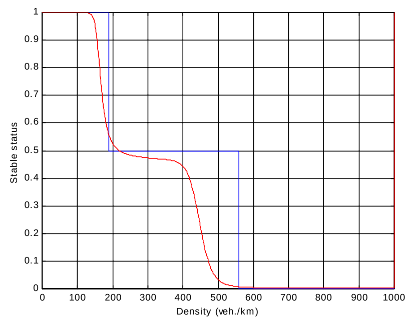

Fig. 11 Backpropagation Neural Network to Classified the System Stability

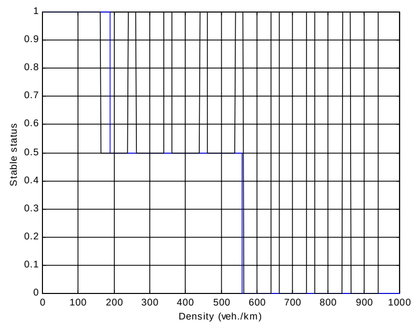

Fig. 12 Ten Training Data of PBDNN to the Classification of System Stability

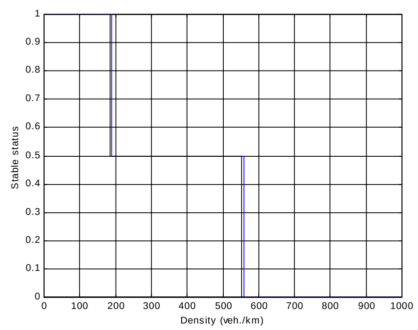

Fig. 13 Thirty Training Data of PBDNN to the Classification of System Stability