Intelligent Algorithm Design of Airbag Based on Genetic Neural Network

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***Abstract*—Airbag control algorithm was designed based on the genetic neural network algorithm for solving the automotive airbag malfunction. Firstly vehicle finite element model and multi-rigid-body model of occupant restraint system for a certain car were established and validated. Then through simulation analyses, the airbag ignition strength and ignition time were determined. Secondly controller hardware platform and software processes were built based on the genetic neural network algorithm. The simulation experiment showed that: the airbag control algorithm could correctly identify the collision intensity and control the error ignition time in 3ms.**

Keywords-Intelligent; Airbag; Genetic Neural Network; Algorithm

I. Introduction

According to the survey from America, there were more than 1400 persons including 600 children died as a result of airbags [1]. Most of the airbag accidents are caused by the malfunction of airbag controller including the false ignition and no ignition. Airbag ignition algorithm is the core of the airbag technology. In recent years, peak acceleration method, Acceleration gradient method, Velocity change method, moving window method, power-rate method and ARMA are common studies on the algorithm. Acceleration gradient method, moving window method and power-rate method are widely used but in poor performance at the aspect of anti-interference which makes airbag work in wrong time. ARMA model prediction algorithm needs establish precise model while it is hard to build precise model in non-linear system.

In recent years, intelligent algorithms have been booming such as neural network, genetic algorithm, fuzzy system and particle swarm optimization which are widely used in intelligent control and industry. Liu Jie and Sun Ji-Gui in Jilin University designed a new control algorithm of airbag which was based on the BP-ANN (Back propagation-Artificial Neural Network) algorithm [2]. This algorithm model could predict the head displacement through the input of the collision data. But this algorithm model doesn't consider the airbag ignition strength and whether occupant is wearing the seatbelt or not. YU Qun-Ming and Qin Meng-Su in Hunan University designed a control algorithm based on the fuzzy neural network which could gain the impact strength and airbag ignition time through the collision data [3]. But the whole algorithm is based on the virtual platform and no actual controller test. Based on previous studies, in this paper the neural network and genetic algorithm were used together in airbag control algorithm. According to the simulation of a certain car's finite element model and Multi-rigid-body model of occupant restraint system, the impact thresholds and the precise ignition time were determined.

II. Genetic Neural Network Algorithm Model

A. Artificial neural network

Artificial neural network (ANN), an intelligent algorithm developed rapidly recently, is an information processing mathematical model imitating the brain synaptic connection structure. BP (Back Propagation) neural network and its variation are basically adopted in most applications of the neural network at present. BP neural network is a forward neural network of error back propagation. Each layer of neurons only affected by the last layer of neurons in the process of signal forward propagation, the network starts back propagation and amends its connection weights when the output of the network and the expectation exceeding a set threshold, and the error signal become smaller in a particular learning algorithm. The structure of BP neural network diagram, as shown in Figure 1, contain three layers. The first layer is the network input layer, second layer of hidden layer, the last layer output layer. The hidden layer can contain multiple neurons and usually adopt LOGSIG transfer function, and the output layer use linear transfer function. The BP network learning is a training of supervision, during which the input vector and the expected output need to be provided.

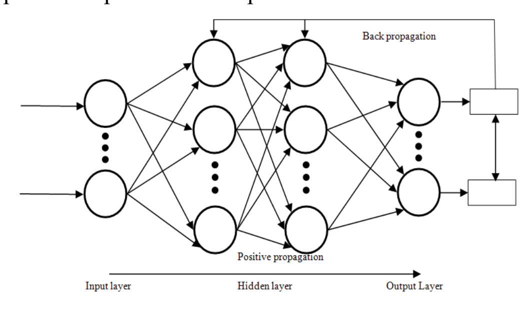

Figure 1. Structure of BP neural network

In the case of 2-layer neural network model, the number of the input layer is set to M, with m represents any input. The hidden layer contains J layers of neurons and each neuron is represented by j. The output layer contains P layers of neurons and each output is represented by p. each weight of the node between input layer and hidden layer is represented by w_{mj} and the weight between hidden and output layer is represented by w_{jp}. The input sample is set as X=[X1,X2,…,XN], and

978-0-7695-4932-3/12 $26.00 © 2012 IEEE
DOI 10.1109/ICTMA.2013.160

each sample is defined as Xk, and each expectation output is defined as dk while the real output is defined as Yk. n stands for the number of iteration. The output of the j neuron in hidden layer is:

$$v_j = f\left(\sum_{m=1}^{M} \mathbf{w}_{mj}\, x_{km}\right) \qquad \text{Y1Y}$$

The output of the p neuron in output layer, i.e. the output of the network is:

$$y_{kp} = f\left(\sum_{j=1}^{J} w_{jp}\, v_j\right) \qquad \text{Y2Y}$$

The summary error of all the output layer neurons is:

BP neural network use gradient descent learning rule and the modified equation of the weight is:

η stands for the efficiency of study.

B. Genetic neural network algorithm

A global optimal solution can't be got since the BP neural network in the training process may be trapped in local minima because of the limitation of training samples and the instability of network. However, as an optimal search algorithm, genetic algorithm could realize global optimization search in complex space with strong robustness. Therefore, better results could be reached when the algorithm is applied to the training of neural network weights. It overcomes lots of drawbacks of the BP algorithm such as low efficiency, slow convergence speed and the situation of easily falling into local optimum, and obtains the most basic features of training samples.

The neural network parameters to be optimized are coded in genetic algorithm, obtaining new generation group after calculation through genetic operators including selection, crossover and mutation. The individual of the new generation which meet the requirements through specific fitness function has been retained. The fitness of new generation is improving constantly with the retained individual continuously carrying out the operation until the requirements of the stop condition have been reached. Neural network parameters are optimized with genetic algorithm in this paper. Coding the neural network weights and bias in genetic algorithm model and decoding the optimal solution as the initial value of neural network training, the neural network use its own advantages to search the optimal solution in local range. Here is the arithmetic process of genetic neural network.

1) Coding the weights and bias in real number, initializing the group P(0) and setting the value of genetic operator;

2) Obtaining the weights and bias of neural network by decoding the new generation individual P(T) and reserving individual through fitness function f(i), which is the reciprocal of sum square E(i) of the differential between the actual output and the expected output of the network. The expressions of f(i) and E(i) are as shown in equation 5.

$$f(i) = \frac{1}{E(i)} \qquad \text{Y5Y}$$

3) Getting the new generation of individuals P(t+1) with genetic calculation as selection, crossover, mutation for the individual of retention in a certain probability;

4) Repeating step 2 and 3 until the end condition is reached;

5) Decoding the optimal network parameters as the initial value of neural network for further optimization;

6) Stopping training when the target of neural network training is reached.

III. SIMULATION MODEL BUILDING

Integrated VOR (Vehicle-Occupant-Restraint system) collision simulation analysis model is established according to the data of a certain vehicle model [4]. The finite element grids are meshed in HYPERMESH with the geometric model which is not including occupant restraint system in order to reduce the calculation amount of simulation. Simulation data of vehicle frontal impact is obtained through the LS-DYNA collision analysis.

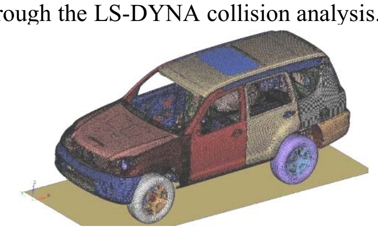

Figure 2. Vehicle finite element model

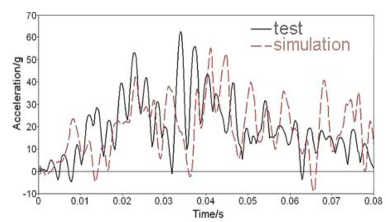

Figure 3. Comparison of acceleration of B pillar between experiment and simulation

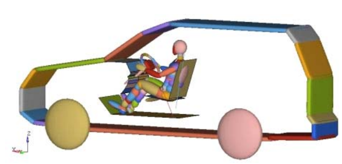

Figure 4. Multi-rigid-body model of restraint system

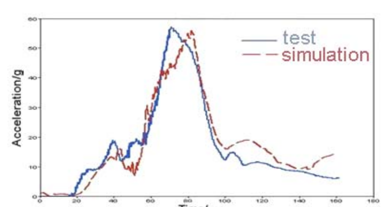

Figure 5. Comparison of acceleration of B pillar between experiment and simulation

The finite element model of vehicle is shown in figure 2, and the comparison of acceleration of B pillar between actual collision experiment and finite element simulation is shown in figure 3. The both curves have the consistently trend and the difference of the peak are not more than 10%. Multi rigid body model of occupant restraint system is build in the MADYMO. Figure 4 shows multi-rigid-body model of restraint system. Figure 5 shows the comparison of head acceleration between test and multi rigid body simulation, from which the difference of the value and the appearance time of the peak are both in 15%.

In this paper, vehicle body acceleration values under different impact velocities are obtained through finite element simulation analysis. Then the vehicle collision data is loaded into multi-rigid-body dummy body, obtaining the dummy head injury value and head movements as the data foundation for follow-up algorithm.

IV. Intelligent Control Algorithm Design

A. Collision threshold selection

According to the calculation of established VOR collision simulation model, vehicle body accelerations at different speed are obtained as shown in figure 6 and the acceleration curves are loaded to 50th percentile multi-rigid-body dummy. The displacement of dummy head is shown in figure 7.

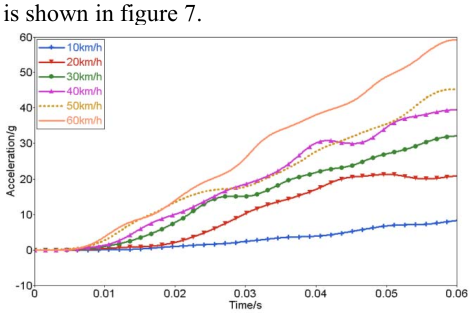

Figure 6. Body acceleration at different speed

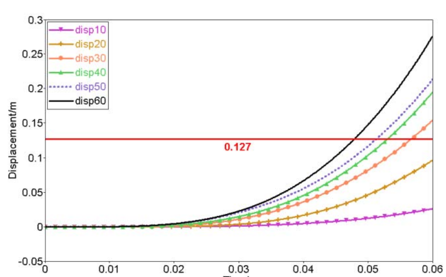

Figure 7. Dummy head displacement at different speed

According to FMVSS 208(Federal Motor Vehicle Safety Standard 208), the passenger head injury value HIC (Head Injure Criteria) must be less than 1000. In this paper, through simulation analysis it can be concluded that if drivers wear seat belt in the appropriate way and the vehicle is in frontal collision at the speed of 15km/h, the drivers' head moves forward and gets in touch with steering wheel leading to a relatively high acceleration peak, but HIC will not exceed the value in regulation.

Table 1. Ignition threshold selection

Without seat belt		With seat belt	
Less than 10km/h	No ignition	Less than 15km/h	No ignition
10-16km/h	determined	15-28km/h	determined
Higher than 16km/h	Ignition	Higher that 28km/h	Ignition

HIC will exceed the regulation required value to 1184 when the collision speed is up to 30km/h. If there is no constraint on passengers without seat belt, after vehicle impact the body moves forward leading to the collision between head and interior parts. When the speed is 16km/h, The HIC reaches to 952, close to the limitation of regulation requirement. The precondition of airbag ignition is shown in table 1: the speed threshold is the collision speed between car and rigid wall [5].

B. Ignition algorithm design

The principle of choosing ignition time is the 127mm-30ms principle: in general, distance between driver and airbag deployment is 127mm, time between trigger and complete deployment is 30ms, the optimal protection of airbags is when occupants touch with airbags and airbags are just right in complete deployment [6]. As it is said, the airbags must be triggered before 30ms when the occupants' displacement is 127mm. According to the 127mm-30ms principle, in frontal rigid collision at speed of 20km/h, 30km/h, 40km/h, 50km/h and 60km/h, the trigger time is 34ms, 27ms, 23ms, 21ms, 18ms after the collision moment respectively. This is shown in figure 7. For the speed higher than 50km/h, the airbag must be triggered in 20ms. This will lead to the input data less than the neural network need and cannot be predicted by the work. So for the high speed collision a new method to predict the ignition time is developed.

Acceleration of the time derivative in the different collision speed is as shown in figure 8. Setting acceleration of the time derivative as DIFF_ACC=da/dt. In a high-speed collision, DIFF_ACC rose rapidly and reached a peak in 10-15ms. This article to judge a high-speed collision conditions are:

1) Sampling acceleration a>3g in five consecutive times before the peak;

2) Acceleration gradient DIFF_ACC >12000 (m/s^3);

3) Sampling acceleration a>5g in eight consecutive times after the peak.

Whether there is a high-speed collision and trigger the airbag depends on the above conditions. With the above conditions, at speed of 40km/h, 50km/h and 60km/h, the trigger time is 19ms, 20ms, and 22ms after the ignition. The error of optimum ignition time is less than 1ms.

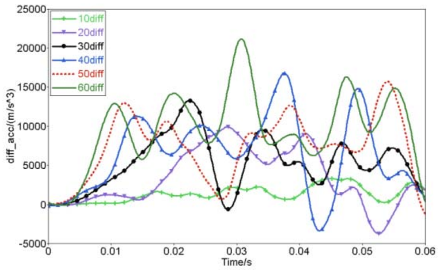

Figure 8 Acceleration gradients at different collision speed

For the Medium-speed and high-speed collision in this paper, former 20ms collision data is selected for the input of Neural Networks. Frequency of ECU collecting acceleration is 1 KHz, that is to say the number of Neural Networks input is 20. The collision strength and occupant head displacement is predicted through Neural Networks [7]. The predictive output of collision strength is the relative speed v in rigid collision, and the predictive output of head displacement has 40 data points. According to the expression 6:

$$j = \sqrt{M + P} + a \qquad \text{Y6Y}$$

J is the number of hidden layer neurons, M is the number of input layer neurons, P is the number of output neurons, a means a constant in [1, 10]. In this paper, J=10. Final network structure: 2 layers BP Neural Networks, M=20, the number of hidden layer is 10, P=40. LOGSIG function is used as transfer function, linear output as output function and TRAINLM algorithm as learning algorithm. According to the neural network model, the parameter of weights and bias of neural network has a total number of 20 × 10+10 × 40+10+40=650. Through coding each parameter into real number and Generating an initial population in genetic algorithms, a group of relatively optimal network weights parameters is obtained. Then using corresponding decoding principle to put the optimal solution into the network structure for neural network training, a group of optimal network weights parameters would be obtained.

V. Test verification

A. Airbag controller design

In this paper an airbag controller was designed based on above algorithm. The controller includes A/D unit, communication unit, storage unit, acceleration sensor unit, ignition unit, power management unit, etc [8][9]. The software structure of controller determines the efficiency of proceeding data and the execution capability of data. The article uses C and assembly language together to improve the execution efficiency. When the system is running, it will initiate the airbag controller and do self-examination at first. The controller will examine whether there is short circuit and open circuit, and when meeting unforeseen circumstances, ignition unit will lighten corresponding light to inform the driver. When the controller has completed self-examination successfully, the master chip collects the vehicle acceleration signals constantly and calculates them. When collision happened, the master chip send ignition signals to ignition chip to detonate corresponding safety devices and store the collision information of airbag in the chip.

B. Algorithm verification

The collision acceleration curve of the model at 35km/h is obtained through finite element simulation and is input to signal generator which provides external acceleration signal to ECU (Electronic Control Unit). Using the ECU communication unit to send airbag ignition information, the predictive strength of collision is 32km/h and the contrast between predictive movement of airbag head and simulation result is shown in figure 9. Error of predictive ignition time is 3ms. It can save cost in the former development in the way of simulation verification.

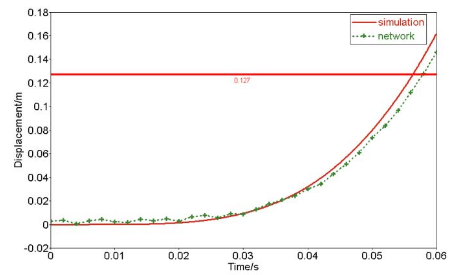

Figure 9 Head displacement output contrast between test and simulation

VI. Conclusion

According to the simulations of finite element model and multi-rigid-body of the occupant restraint system model of a certain vehicle, the collision threshold and ignition time of airbag were determined in the current paper. Through building genetic neural network algorithm model and using the former 20ms data of collision as network input parameters, the collision strength and occupant head displacement were predicted by the neural network calculation. Based on the above algorithm, an intelligent airbag controller was developed and then tested by experiment. The test result showed that the controller could recognize collision strength correctly and control the error ignition time in 3ms. Next step is to take real vehicle road test and real vehicle collision test to make sure the intelligent airbag controller have strong anti-jamming and execution capabilities.

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