Research on Virtual Reconstruction of Vehicle Crash Accident Using FEM and Neural Networks

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Abstract: The objective of vehicle crash accident reconstruction is to achieve the pre-impact velocity. Elastic-plastic deformation of the vehicle and the collision objects are the important information produced during vehicle crash accidents, and the information can be fully utilized by the finite element method, which has been widely used as simulation tools for crashworthiness analyses and structural optimization design. But the FEM is not practical in accident reconstruction because the FE models are getting bigger, which increases the simulation time and cost. The use of neural networks as global approximation tool in accident reconstruction is here investigated. Neural networks are asked to map the relation between the initial crash parameter, that is, the velocity and deformation. The inputs and outputs of the ANN for the training process are obtained by explicit finite element analyses performed by LS-DYNA3D. The procedure is applied to a typical traffic accident: the deformation of the key points on the frontal longitudinal beam and the mudguard could be measured according to the simulation results; These results could be used to train the neural networks adapted back-propagation learning rule; The pre-impact velocity could be achieved by the trained neural networks, which can provide a scientific foundation for accident judgments.

Keyword: Vehicle, Computer simulation, Accident Reconstruction, Finite element method, Neural networks

1 Introduction

Vehicle accidents bring dramatic tragedy to people and have become severe social problems that threaten people and their property at an accelerating rate, particularly in developing countries such as China. Vehicle collision analyses and accident reconstructions have become increasingly popular in recent years due to the seemingly expanding rate of civil litigation. The most concern of vehicle crash accident reconstruction is to achieve the pre-impact velocity [1].

The whole process of a vehicle accident can be divided into three phases: (1) Post impact - the usual starting point of the reconstruction developed from information obtained from the accident scene. (2) Impact - determination of the vehicle's impact speeds, impact directions and impact location, and so on. (3) Pre-impact - determination of speeds and trajectories (usually the unknowns). The main method of accident analyses is to find out the vehicle motions in collision phase through vehicle rest positions in post-collision phase, and then the vehicle motion in pre-collision phase, based on the collection, recording, investigation and analysis of the accident scene.

Due to the variety, complexity and instantaneity of the traffic accidents, the precision of doing quantitative analyses of accidents manually is quite low. To traffic accident, the objective is the pre-impact velocity and trajectory. Elastic-plastic deformation of the vehicle and other collision objects are the important information of vehicle crash accidents. But the computer programs now available for the reconstruction of vehicle accidents seldom consider the deformation [2]. With the development of simulation technology, the finite element method that can fully utilize the deformation plays an important role for the reconstruction of vehicle crash accidents. The explicit finite element algorithm using a very small integration time step takes not only the strain rate of materials in high

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speed but also the elastic and plastic characteristics into consideration [3]. So, researches on reconstruction of vehicle accidents based on the finite element method can achieve a relatively high precision of calculation. In addition, for an effective presentation of the results, 3-D animations can be created using the post-processing software based on the finite element method. At the same time, direct observations of the deformation behavior of key energy absorbing parts, such as mudguard and the front longitudinal beam, in different types of accidents can be taken. This can't be finished well by other accident reconstruction programs. Nevertheless, the finite element method have never got good applications in accidents reconstruction due to the crash simulation time is too long.

Therefore, this paper deals with the development of crash accident reconstruction technique by using neural network and the finite element method. In the present method, the non-linear explicit finite element code LS-DYNA3D is adopted to simulate the crash accidents. On the basis of the numerical results of the crash accidents, a three-layer feedforward neural network is applied to generate an approximated function of the initial crash parameter and the deformation index E. The approximated function of E is then maximized under velocity and angle constraints by generic algorithm. The procedure is applied to a typical traffic accident: the deformation of the key points on the frontal longitudinal beam and the mudguard could be measured according to the simulation results; These results could be used to train the neural network by back-propagation learning rule; The pre-impact velocity could be achieved by the trained neural network, which can provide a scientific foundation for accident judgments.

2 Nonlinear Finite Element Method and Neural Networks

2.1 Basic nonlinear explicit finite element method

For a point in a body, the time-dependent deformation can be found by seeking a solution to the momentum equation [4]:

$$\sigma_{ij,j} + \rho f_i = \rho \ddot{x}_i \tag{1}$$

where σ_{ij} is the Cauchy stress, ρ is the current density, f is the body force density, $\ddot{x}_i$ is acceleration. By using the divergence theory it can lead to a statement of the principle of virtual work, i.e.:

$$\int_V \rho \ddot{x}_i \delta x_i dV + \int_V \sigma_{ij} \delta x_{i,j} dV - \int_V \rho f_i \delta x_i dV - \int_{S^2} t_i \delta x_i dS = 0 \tag{2}$$

The structures and components can be modeled by many elements. The geometry of the element is represented by Lagrangian description that is in terms of shape function. Thus equation (2) becomes the matrix form:

$$\sum_{i=1}^{n} \{ \int_\upsilon \rho N^t N a d\upsilon + \int_\upsilon B^t \sigma d\upsilon - \int_\upsilon \rho N^t b d\upsilon - \int_A N^t F dA + \int_s N^t F_c ds \}^i = 0 \tag{3}$$

where n is the number of elements, N is an interpolation matrix, σ is the stress vector, B is the strain-displacement matrix, a is the nodal acceleration vector, b is the body force load vector, and F is applied traction load. After assembly, equation (3) can be written at time t:

$$M\ddot{u}_t + P_t - F_t + R_{ct} = 0 \tag{4}$$

where M is the mass matrix, $\ddot{u}_t$ is the nodal acceleration vector, P_t is the internal force vector, F_t is the external applied loads, F_{ct} is the contact force.

To solve equation (4) efficiently, the explicit central difference method is used usually. To advance to time $t + \Delta t$, the central difference equations can be given:

$$\dot{u}_{t+(\Delta t/2)} = \dot{u}_{t-(\Delta t/2)} + \Delta t \cdot \ddot{u}_t$$
$$u_{t+\Delta t} = u_t + \Delta t \cdot \dot{u}_{t+(\Delta t/2)} \tag{5}$$

according to equation (4) and (5), the displacement at time $t + \Delta t$ may be written as:

$$u_{t+\Delta t} = M^{-1}[(\Delta t)^2 (Q_t - F_t + F_{ct}) + 2Mu_t - Mu_{t-\Delta t}] \tag{6}$$

where Δt is time step, $t + \Delta t$ and $t - \Delta t$ refers to current and previous time increments, respectively. The elemental mass is lumped at the nodes, so that the mass matrix, M , is diagonal. Equation (6) becomes some unrelated equation group, which leads to the solution more efficient. Whereas, the finite element models for crash simulation contain very large number of elements and time step of explicit central difference method is small, the computing time is considerable long.

2.2 Back-propagation neural networks

Neural networks [5] as global approximation tool has been widely used because of their ability to process and map external data and information basing on past experience. In a neural network the transmission and the processing of the input data are assigned to a net of simple computing units called neurons. Each neuron returns an output signal when the weighted sum of the inputs exceeds an activation value. The output value is computed by defining a transfer function, also called activation function.

In this research a feedforward multilayer neural network is used. The network consists of a first neuron layer, one or more hidden layers and an output layer as sketched in Fig 1. The first layer, called input layer, receives the external inputs and transfers signals to the hidden layers. The signals are modified, weighted and redistributed throughout the hidden layers till the output layer. The output signal of the i th neuron of the k th layer can be computed as:

$$out_{k,i} = f_k(\eta_{k,i}) \tag{7}$$

where f_k denotes the transfer function of the considered layer. A sigmoid function is used for the neurons of the hidden layer, the function can be written as:

$$f_k(\eta_{k,i}) = \frac{1}{1 + e^{-\eta_{k,i}}} \tag{8}$$

and the neurons of the output layer use a linear transfer function as:

$$f_k(\eta_{k,i}) = \eta_{k,i} \tag{9}$$

where $\eta_{k,i}$ is the activation signal of the ki neuron. The activation value is computed as:

$$\eta_{k,i} = \beta_{k,i} + \sum_{l=1}^{N_{k-1}} \omega_{k,i}^{l} \cdot out_{k-1,i} \tag{10}$$

where N_{k-1} is the number of neurons in the previous layer and therefore it is equal to the number of links of the ki neuron. $\omega_{k,i}^{l}$, with $l = 1,....,N_{k-1}$ and $\beta_{k,i}$ are respectively the link weights and the bias value of the considered neuron.

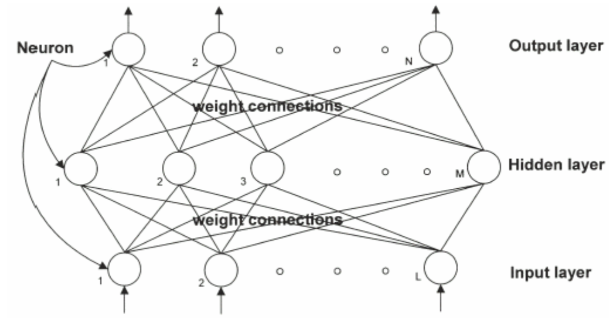

Fig.1 The architecture of tree layer feedforward neural network

The learning process of the neural network involves a finite number of examples, the training set, characterized by input-output pairs known a priori. The link weights and the bias value of the neural network are changed so to minimize the differences between the known and computed output. The neural network uses the back-propagation learning rule where the RMS between the known and computed outputs is minimized. The training process is performed using the Levenberg-Marquardt algorithm. The algorithm was originally designed for least-squares minimization where the objective function is defined as a sum of square. As thus the objective function results always non-negative.

A batch mode is used to perform the training process. For each output of the neural network a single average square error is defined as the sum of the RMS errors attained by each case of the training set. Indeed, considering a training set of N input-output pairs, the error to be minimized is defined as:

$$RMS = \sqrt{\frac{1}{N} \cdot \sum_{n=1}^{N} (t_n - o_n)^2} \tag{11}$$

where t_n is the known output and o_n the corresponding value computed by the network. The use of batch training allows the learning process to be faster and reduces the probabilities to find a local minimum.

In order to improve the speed and the efficiency of the learning phase, the input and output data are scaled. Herein, the input data are linearly scaled between 0 and 1 using the equation:

$$x = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{12}$$

where x is the scaled value of the design variable vector X, where $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the design domain respectively.

The input variables of the neural network are chosen to describe the velocity and angle of the considered structure while the output values are mainly related to the deformations.

3 Accident reconstruction using FEM and neural networks

According to characteristics of crash accidents, the indices to evaluate the accident were given as $x_1, x_2, ..., x_n$, which reflected the deformation of the key points in the main energy-absorbing parts during the crash. The key points were chosen at the round hole and the bolthole, which were easy to locate. The deformation of the center of the round hole can be measured using the deformations of the 3 points on the circle of the hole and the deformation of the bolt hole can be measured using the information of three coordinates of the nodes in that place.

Using the measurement values of these indices from the survey of the accident scene: $x_{1e}, x_{2e}, ..., x_{ne}$ and the calculation values of these indices from computer simulations: $x_{1c}, x_{2c}, ..., x_{nc}$, the index E is defined to reflect the difficulty level of accident reconstruction.

$$E = 1 - \left(\Sigma\left(x_{ie} - x_{ic}\right) \cdot \left(x_{ie} - x_{ic}\right) / \left(\Sigma x_{ie} \cdot x_{ie}\right)\right) \tag{13}$$

Obviously, E is closer to 1, and the crash reconstruction by computer simulation is closer to the real situation. So the equation to calculate the index E is set as the object function, the initial velocity and angle of the car are set as the variables, which would be optimized. That is to choose a right combination of the initial velocity and angle of the car to make the index E the maximum.

How to maximize the index E is a process of repetitious computer simulations. The combination of computer simulation and neural network modeling is an enabling technology for crash reconstruction in shorter time. The finite element analyses are used to generate the examples for the training and test sets of the neural network and are performed using the commercial code LS-DYNA3D. The trained neural network can map the relation between the variable, that is, the initial velocity and angle of the car, and the objective function, that is, the index E. The settlement of the training patterns is performed by the technique of design-of-experiment in order to obtain a homogeneous allocation inside the normalized domain. The maximum of the index E is achieved using a generic algorithm utilizing the trained neural network predictor.

4 Application to a typical traffic accident

4.1 Traffic accident scene.

The procedure described above has been applied to an accident happened to one car in Hai Nan province, China in December 2001 as shown in Fig.2, the geometry of the wall is measured. Three-coordinate-measuring instrument is used to measure the deformation of the car body. First the "body ordinate system" is set at the back of the car, where there is no deformations, then 11 key points are selected at the front of the car where major deformation occurred: 7 bolt hold on the frontal longitudinal beam, 4 round hole on the mudguard. Because these two main energy- absorbing parts are hardly affected by the rough surface of the wall, they should be more reliable than the front wall. Fig. 4 is the geometry of the frontal longitudinal beam and the fender, and the coordinates in Fig.4 are the three-dimensional coordinates before deformation.

Fig. 2 Scene of one accident

Fig.3 Measure the deformation of auto-body

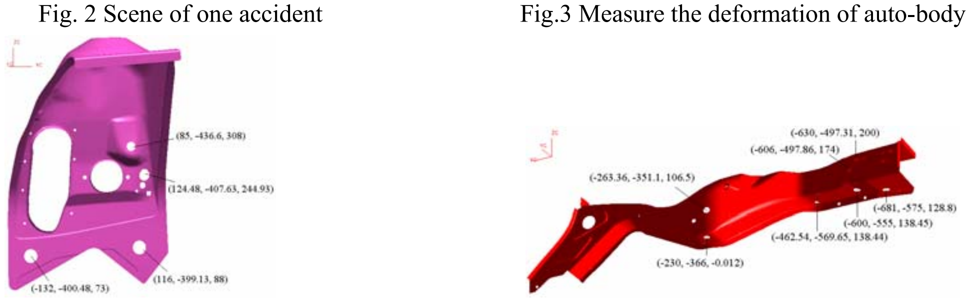

Fig.4 CAD model of the energy-absorbing parts

4.2 Finite element modeling

The vehicle model is first disassembled and grouped into several main groups: the frame, front inner, cabin, doors, etc. The three dimensional geometric data of each component are obtained by using UG and Catia software. Next, these files are imported into Hypermesh software for meshing and model assembly. Finally, the model is translated into LS-DYNA3D input files. It is known that the total structure is made up of more than 130 parts, which are connected by joints (including spot welding, arc welding), bolt connecting, rivet connecting and adhesives gluing. Many types of elements are used to describe the geometric shapes, connecting properties etc, including shell element, beam element, rod element, hexahedron element, spring element, rigid nodes and specific welding nodes which can fail when some specific conditions are met.

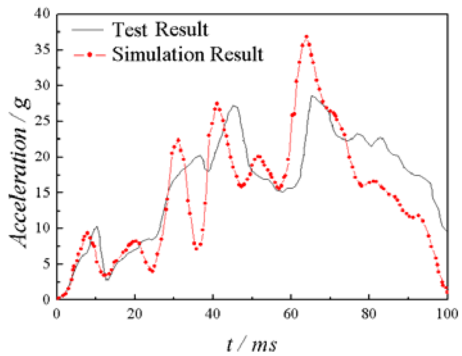

Fig.5 Acceleration curve of sub floor by FEM simulation and experimental result

A 3-D dummy model used to simulate the dynamic behavior of the occupant in the full frontal crash, is created. All parts of the model are connected using spherical and revolute joints. The numerical model is also validated by means of experimental results according to CMVDR294. Fig.5 shows the comparison between the experimental and the numerical acceleration-time curve [6-7]. During the experiment and FEM simulation, the impact velocity is 48.3km/h.

In this simulation, the deformation of the engine is not considered, but is treated as a rigid part. The doors are connected to the body using hinges and door locks. According to the photo of the traffic accident scene, the finite element model of the wall is also included in the whole model.

Fig.6 shows the finite element model of the commercial vehicle and the wall. Fig.7 shows the finite element model of the mudguard and the front longitudinal beam.

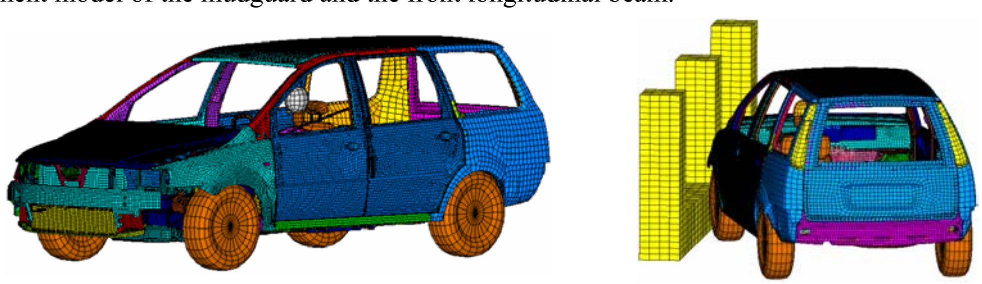

Fig. 6 Finite element model of the commercial vehicle and the wall

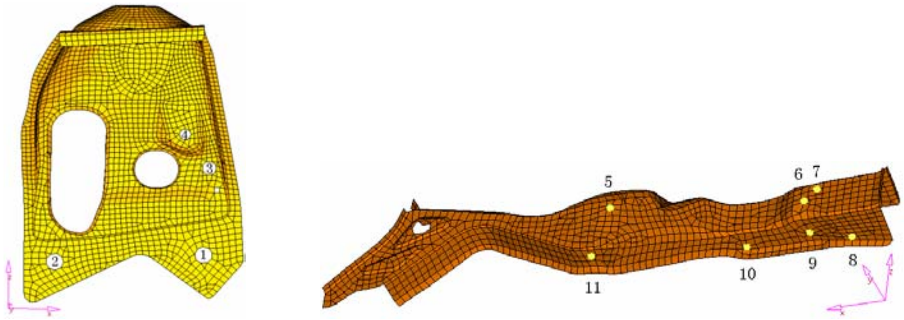

Fig. 7 Finite element model of the mudguard and the front longitudinal beam

4.3 Accident reconstruction

The measurements of the deformation of the longitudinal beam and mudguard are listed in the table 1.

Table 1 the measurements of the deformation of the key points

No.	1	2	3	4	5	6	7	8	9	10	11
Measurements (mm)	18.9	18.7	16.9	16.3	47.4	207.6	209.6	260.3	140.6	210.9	86.1

The velocity and direction of the commercial vehicle are taken as design variables, and the upper and lower bounds of the design variables are restricted as

$$38km/h \le V \le 78km/h$$

$$5^{\circ} \le \theta \le 25^{\circ}$$

As shown in table 2, six design levels of each design variable have the same intervals, respectively.

Table 2 design variables and design levels in the design domain

Design variables	Design levels					
Velocity $V\ (km/h)$	38	46	54	62	70	78
Direction $\theta\ (\deg)$	5	9	13	17	21	25

The training set consists of a total number of 36 points in the design domain, and the test set consists of 4 points randomly chosen inside the design domain. A total number of 40 LS-DYNA3D runs are then performed. The average CPU time required for a single finite element analysis is about 8 hours using 4 CPUs of SGI onyx3800 shared-memory parallel computer.

The data of deformation of the eleven key points and the index E are calculated for each simulation as the output value of the neural network described above. The training parameter mainly includes the learning rate and momentum constant. Their values are 0.25 and 0.50, respectively. The neural network converges to an acceptable RMS error value of 1E-03 after about 1400 cycles.

Table 3 comparisons between E obtained by FEM simulation and by the neural network

Test points	Velocity (km/h)	Direction ($\deg$)	E (Numerical results)	E (Neural network results)
1	46	11	0.53	0.51
2	58	13	0.84	0.83
3	40	21	0.61	0.60
4	62	19	0.70	0.68

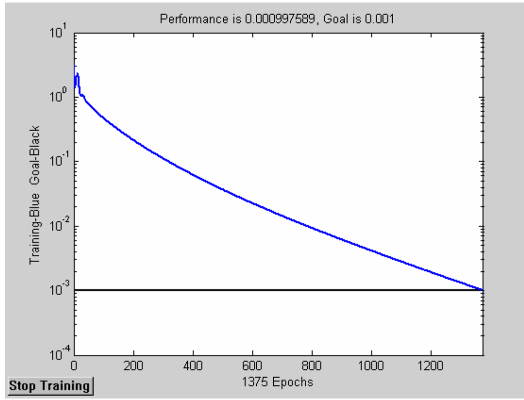

Fig. 8 The training curve of neural

From table 3, we find that the neural network can be able to map the relation between the initial crash parameter and the deformation index E in accurate manner. The maximum of the index E is achieved using a generic algorithm utilizing the trained neural network. The velocity and angle corresponding to the maximum of the index E are $51km/h$ and 16° respectively. The simulation result is shown in Fig 9. It can be said that the simulation with the combination of the velocity and angle is quite coincident with the real accident.

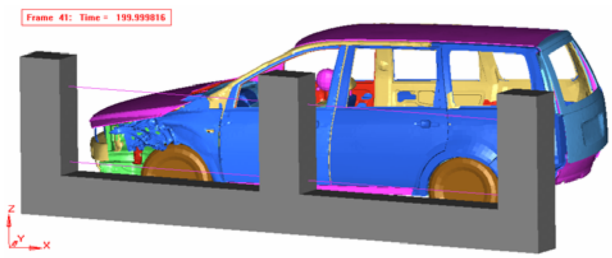

Fig.9 Simulation result of 16° and 51km/h

4.4 Result verification

Because of the clear tire marks on this accident scene, we can get the model of these marks by making use of photogrammetry technique by solving the collinear equations to obtain the object points set (see Fig. 10). So the angle between the direction of vehicle motion and the plane of wall can be measured from this model, and its result is 16.89º. Then this model would be imported into the PC-CRASH, one accident reconstruction software, and the velocity before the vehicle impacted the wall could be computed, the data is 51.3km/h. This is very close to the result obtained by the FEM. But the method mentioned above doesn't utilize the information of vehicle deformation. It relies on the tire marks thoroughly. It's well known that nowadays many vehicles are installed with ABS so that the tire marks can hardly be got after braking. Furthermore, the weather condition or people can destroy tire marks easily. FEM resolve the velocity and angle according to vehicle deformations, and doesn't need any exterior conditions such as the tire mark. So more reliable results could be got with the finite element method.

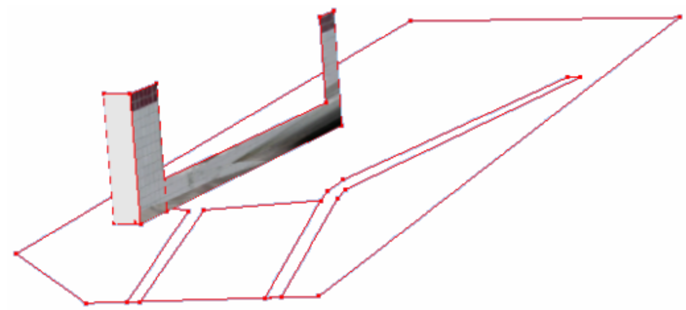

Fig.10 Solving the direction of movement by photogrammetry

5 Conclusions

This paper proposes a new technique to reconstruct crash accident using the finite element method that has been widely used as simulation tools for crashworthiness analyses and neural networks as global approximation tool. Using the FE simulation, the elastic-plastic performance and strain rate takes into account adequately, so its result is more accurate. Using the neural network, the relation between the initial crash parameter and the key points' deformation is mapped correctly, so it reduces the number of FE simulation. The procedure is applied to a typical traffic accident. The simulation with the pre-impact velocity and angle achieved by the trained neural network are coincident with the real accident, which can provide a scientific foundation for accident judgments.

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