Proceeding of the 13th International Forum of Automotive Traffic Safety, 2016, pp 507-513
No.ATS.2016. 507

Prediction of Pedestrian Chest Injury Severity using BP Neural Network

Wenjun Liu [1], Yongyong Zhang [2] , Aowen Duan [1], Jinlong Qiu [1] and Zhiyong Yin [1*]
[1] *Institute for Traffic Medicine, Department 4th, Institute of Surgery Research, Daping Hospital, Third Military Medical University, Chongqing 400042, China,*
[2] *Transit College, Chongqing Jiotong University, Chongqing 400074, China*
E-mail：liuwenjun@dphospital.tmmu.edu.cn

Abstract:

***Background*:** Chest is one of the three commonly injury parts for pedestrians in car-to-pedestrian crashes. Although many efforts and studies have been done on chest injuries, mathematical model relationship between chest injury risk factors and chest injury severity hasn't been widely identified.

***Objective*:** This paper is aimed to investigate and predict the severity of chest injuries caused by car-to-pedestrian crashes though establishing BP neural network prediction models.

***Method and Material*:** This study is carried out by conducting an in-depth investigation of car-to-pedestrian crashes from 2010 to 2014 in Chongqing and applying different training functions and hidden layer nodes in BP neural network training to determine the best prediction scheme.

***Results*:** The study results showed that the training function and the number of hidden layer nodes had great influence on the prediction accuracy of neural networks. The best prediction result for chest MAIS was obtained by using *trainlm* function with 11 hidden layer nodes.

***Conclusions*:** Models presented in the present study reflected the non-linear relationship between the severity of pedestrian chest injuries and the vehicle impact speed and pedestrian age. Furthermore, study results fully testified the feasibility and effectiveness of predicting pedestrian chest injury severity by using BP neural networks.

Keywords: Pedestrian, Chest, Injury severity, Prediction, BP neural network

1 Introduction

With the rapid development of Chinese motorization, about 23,000 people died in traffic accidents every year, accounting for 26% of the total vehicle traffic accident death. Justice, dispute, litigation and other social problems caused by pedestrian-vehicle collisions become more and more serious. Therefore, it is still a noteworthy work to research on the factors and issues related to car-to-pedestrian crashes, such as accident forms, vehicle speeds and pedestrian injuries. As one of the complicated accident analysis problems, pedestrian injuries have increasingly drawn the attention of researchers. Previous studies show that chest is one of the three commonly injury parts for pedestrians in car-to-pedestrian crashes [1]. Serious chest injures will threaten life or cause unpredictable consequences for the victims. Although many efforts and studies have been done on chest injuries [2-5], mathematical model relationship between chest injury risk factors and chest injury severity hasn't been widely identified. Here, one possibility is that the factors associated with pedestrian injuries are complicated due to a number of factors including vehicle such as "type of vehicle", personal characteristics such as "age, gender", environment such as "weather condition" [6].

The role of impact speeds in car-to-pedestrian crash likelihood has been confirmed through numerous studies. That lower mean speeds in response to speed limit reduction result in reduced likelihood of casualty crashes was demonstrated by the studies of Nilsson [7] and Elvik [8]. The fact that even small reductions in speed could lead to considerable reductions in road trauma was also supported by many research. Some researchers have focused on severity of crash outcomes in response to speed. Additionally, that fatal crashes decline more substantially with the same amount of mean speed reduction than all injury crashes was showed in studies of Elvik [8] and Tefft [9]. In other words, severity of crashes decreases with reduced mean speed.

A number of previous studies have largely focused on age categories with regard to injury-severity outcomes of vehicle occupants [10-13]. However, because of direct exposure to crash forces and resulting energy dissipation, the age thresholds should be different for pedestrians. Though extensive empirical investigation, males and females under 50 years old and 50 years old and older were considered as the age categories that determined to provide the best statistical fit. This age split is supported by the effects of age on bone density, muscle mass and muscle strength. With age between 25 to 35 years, pedestrian bone density, muscle mass and muscle strength will reach the highest levels; with age after 50 years, pedestrian bone density, muscle mass and muscle strength will decrease by 12-14% per decade [14]. It can be found that the age-range of this deterioration have obvious influence on pedestrian-injury outcomes.

According to the in-depth investigation of minibus-to-pedestrian accidents conducted by Li [15], two most important factors which have influence on pedestrian mortality are vehicle impact speed and pedestrian age. The proportion of fatalities is significantly higher for elderly than non-elderly pedestrians. And the increasing vehicle impact speed increases pedestrian injury risk. Additionally, the results show that it is hard to estimate the severity of chest injury because of the non-linear and uncertainty. These results are also applicable to car-to-pedestrian crashes.

Artificial neural networks (ANN) are capable of approximating any finite non-linear models to determine the relation between dependent and independent variables. ANN is based on nature of human brains, and it has powerful parallel and adaptive learning ability. Back Propagation (BP) neural network is a part of ANN which has been applied in different areas successfully [16-20]. On the basis of background above, the BP neural network model is established to investigate and predict the severity of chest injuries caused by car-to-pedestrian crashes, with the vehicle impact speed and the pedestrian age as inputs and the severity of chest injuries as output.

2 Method and Material

2.1 Pedestrian Chest Injury Data

A team composed of experienced medical experts, engineers and researchers was formed to investigate the road traffic accidents in Chongqing, China. The team had the ability to collect onsite pedestrian accident data because of the cooperation with the police departments. An in-depth investigation of car-to-pedestrian crashes from 2010 to 2014 in Chongqing was conducted in this study. The selected cases needed to fulfill the following criteria:

1. The pedestrian should be older than 14 years of age.

2. The pedestrian chest should be struck by the hood of car.

3. The impact speed of car-to-pedestrian could be calculated from the braking distance or the pedestrian throwing distance, or obtained from videos or event data recorder (EDR) [21].

4. The chest injury outcomes assessed by the Abbreviated Injury Scale (AIS) should be 1+. Pedestrian injuries were coded according to the Abbreviated Injury Scale which uses 1, 2, 3, 4, 5, and 6 to denote minor, moderate, serious, severe, critical, and untreated injury, respectively.

One hundred and five cases with determined impact speeds and detailed chest injuries were selected to analyze the pedestrian chest injuries. Photos of some cases were shown in Figure 1. In these 105 casualties, there were 59 males and 46 females. The mean age of enrolled pedestrians was 54, and the standard deviation for age was 17. Of the chest injuries, Maximum Abbreviated Injury Score (MAIS) 5 accounted for 12/105, MAIS 4 for 9/105, MAIS 3 for 40/105, MAIS 2 for 27/105 and MAIS 1 for 17/105.

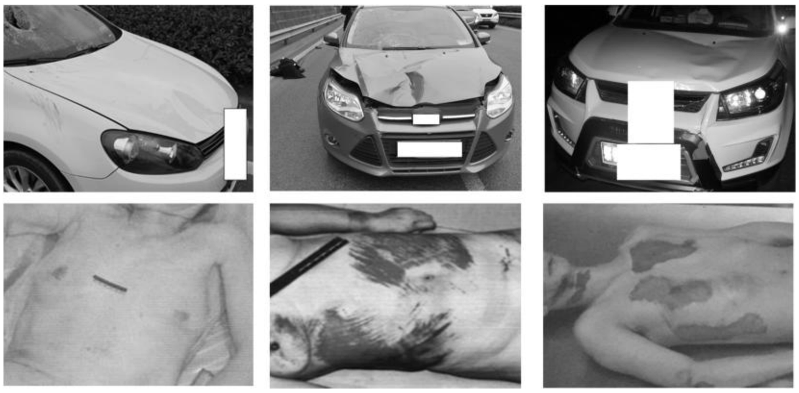

Figure 1. Photos of some cases

2.2 BP Neural Network

The structure of a three-layer BP neural network is represented in Figure 2, which is composed of one input layer, one hidden layer and the output layer. Each neuron in any layer related with the entire next layer neurons through lines contained with coefficients called "weight coefficients". The function of the network would alter with any change in coefficients. In fact, the main goal of the BP neural network training is to find the best weight coefficients to obtain the desired output.

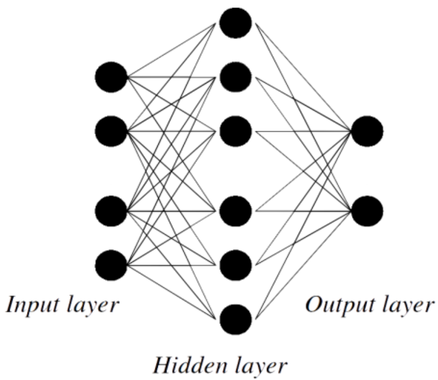

Figure 2. Three-layer BP neural network

In network training, the inputs of the first layer multiplied in weight coefficients that would be any randomly selected number and then enter into the neurons in second layer. Calculating the sum of the inputs and then inserting the sum in a function called" activation function" are the two ways presented in any neuron functions. Hyperbolic tangent and sigmoid factions showed in Figure 3 are the two of most commonly used type for activation functions [22].

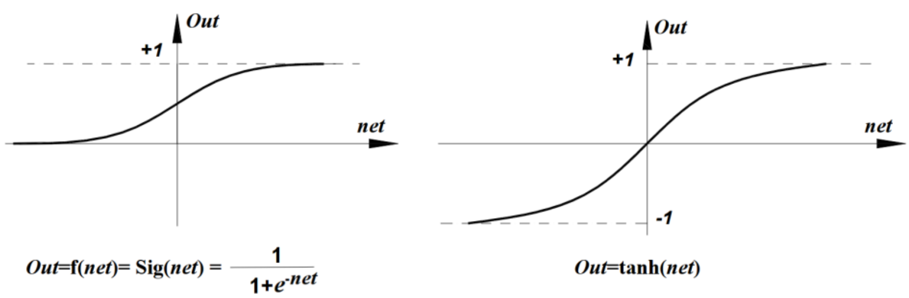

Figure 3. Activation functions

During network learning, the error between target output and network output calculated and again sent from the last layer to the previous one and thus the weight coefficients of network corrected using equations 1, 2. Once again the network generates output, using the new weight coefficients and also calculates the reducing error and back propagates it into the network until the error reaches to its least value that is the desired value, after many epochs.

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_{pi} o_{pj} \tag{1}$$

$$\delta_{pi} w_{ij}(t+1) = w_{ij}(t) + \eta \delta_{pi} o_{pj} + \alpha[w_{ij}(t) - w_{ij}(t-1)] \tag{2}$$

Where:

$w_{ij}(t+1)$: Weight coefficient in step $t+1$, from neuron i to neuron j.

$w_{ij}(t)$: Weight coefficient in step t, from neuron i to neuron j.

η: Learning coefficient.

δ_{pi}: Difference between desired output and network output in neuron p of layer j.

o_{pj}: Output of neuron p of layer j.

α: Momentum coefficient.

$w_{ij}(t-1)$: Weight coefficient in step $(t-1)$, from neuron i to neuron j.

2.3 Establishment of the Prediction Model

2.3.1 Data Normalization

In order to make the forecast data more accurate and eliminate the influence of the dimension of the data itself on the prediction accuracy, the input and output data should be normalized using equation 3 before applying to the network.

$$Y = (X - X_{\min})/(X_{\max} - X_{\min}) \tag{3}$$

Inverse transformation:

$$X = X_{\min} + Y(X_{\max} - X_{\min}) \tag{4}$$

Where:

Y : The normalized data.

X : The raw data.

$X_{\min}$: The minimum value of the input data.

$X_{\max}$: The maximum value of the input data.

2.3.2 Determine the Number of Hidden Layer Neurons

According to the empirical formula $m = \sqrt{n+l} + \phi$, where m, n, l, ϕ represent the number of the hidden layer neurons, the input layer neurons, the output layer neurons and the constant, respectively, n and l should be 2 and 1 in this study, and ϕ was one constant between 1 and 10, therefor m was determined as 3~12.

2.3.3 Selection of the Training Function

Traingdx, traingdm, traingd and *trainlm* are the most commonly used training functions for neural networks. The four functions were used to train the BP neural networks in this study, respectively. And the error analysis of the training results was conducted to determine the best training function.

3 Results

Based on the in-depth investigation of car-to-pedestrian crashes from 2010 to 2014 in Chongqing, literature investigation to determine the two of the most important factors on pedestrian-injury outcomes was used, and the vehicle impact speed and pedestrian age taken as the inputs, the severity of chest injuries as the output, three-layer BP neural network prediction models were established. These networks took tansig function as the activation function and purelin function as the transfer function. Different training functions were applied to neural network training to determine the optimal number of hidden layer nodes and the best training function. The last set of 105 cases was selected as the test sample to test the predicting precision of these models. The prediction results were compared with the actual value, and some partial error analysis are shown in Table 1.

Table 1. Error analysis of chest MAIS prediction using different training functions

Error analysis	m=3		m=6		m=9		m=12	
	Absolute error	Relative error (%)	Absolute error	Relative error (%)	Absolute error	Relative error (%)	Absolute error	Relative error (%)
traingdx	0.1723	17.23	0.1759	17.59	0.1456	14.56	0.2357	23.57
traingdm	0.2741	27.41	0.4110	41.10	0.2664	26.64	0.2618	26.18
traingd	0.2195	21.95	0.0253	2.53	0.1429	14.29	0.1201	12.01
trainlm	0.0560	5.60	0.1334	13.34	0.3197	31.97	0.0857	8.57

The error analysis showed that the training function and the number of hidden layer nodes had great influence on the prediction accuracy of neural networks. For the same training function, no obvious relationship existed between the relative error of the network prediction results and the number of the hidden layer neurons. For the different training function, the optimal number of hidden layer nodes was different.

The prediction accuracy of the model was relatively high for traingd function with 6 hidden layer nodes; while the hidden layer nodes should be set at 3 for trainlm function to obtain an ideal prediction accuracy. In addition, it can be concluded that the prediction accuracy of the model was poor when using traingdx and traingdm functions. Figures 4 and 5 illustrate correlations between desired output and networks predicted output for models using traingd function-6 and trainlm function-3, respectively.

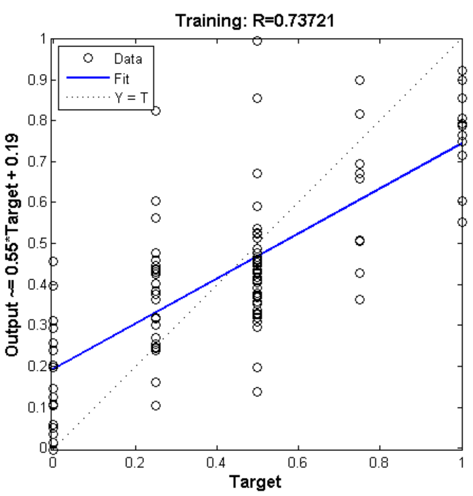

Figure 4. Fitness curve of the model using *traingd* function-6

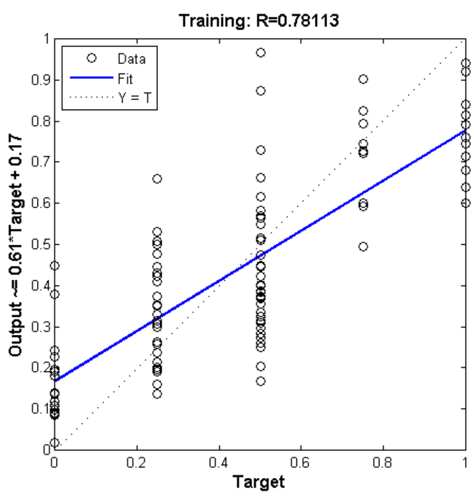

Figure 5. Fitness curve of the model using *trainlm* function-3

A large number of training results analysis showed that the minimum relative error of the prediction results was 1.73%, and it was obtained by using *trainlm* function with 11 hidden layer nodes. The fitness curve of this model is presented in Figure 6.

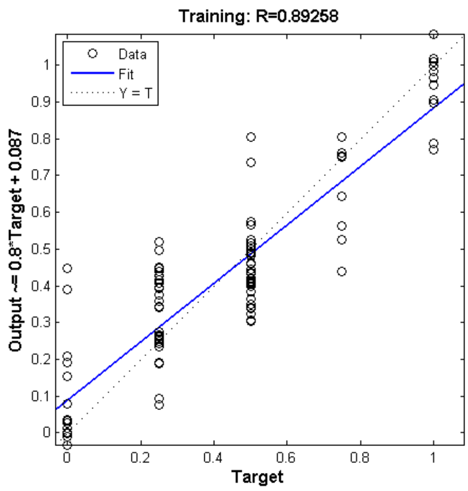

Figure 6. Fitness curve of the model using *trainlm* function-11

4 Conclusions

In this study non-linear BP neural networks have been utilized to predict the severity of pedestrian chest injuries caused by car-to-pedestrian crashes. For this purpose, after referring to relevant materials, two factors that have highest effect in network output (pedestrian chest severity) were selected. On the basis of the in-depth investigation of car-to-pedestrian crashes from 2010 to 2014 in Chongqing, three-layer BP neural network prediction models were established. Different training functions and hidden layer nodes were applied in network training to determine the best prediction scheme. Studies showed that BP neural network which took *trainlm* as training function and set hidden layer nodes at 11 yielded the best results.

There have been no pedestrian chest injury severity prediction models developed in previous researches using BP neural networks that encompassed the simultaneous effects of the vehicle impact speed and pedestrian age. Therefore, models presented in the present study aim to establish such a mathematical relationship. Study results fully testified the feasibility and effectiveness of predicting pedestrian chest injury severity by using BP neural networks. In addition, these models suggest that changes in pedestrian chest injury severity doesn't depend upon the vehicle impact speed or pedestrian age individually, but occur as a simultaneous result of changes of the two factors.

However, there are still some shortcomings that exist in BP neural networks. Because of its poor stability, the results of each training will be different. With the increase of the times of training, the over-fitting problem could occur, which would result in low prediction accuracy. Additionally, there are many factors that have influence on pedestrian-injury outcomes, which cannot be quantified, and it is hard to take all these factors into account. All the above problems would give the directions to improve the models presented in the present study.

Acknowledgement

This work is financially supported by the Natural Science Foundation of China (Project number: 31271006), the Open Foundation of State Key Laboratory of Vehicle Noise-Vibration-Harshness and Safety Technology (Project number: NVHSKL-201409), and the "12th Five-Year Plan" National Science and Technology Support Program (Project number: 2014BAG01B05).

References

[1] Yang J. *Overview of Research on Injury Biomechanics in Car-pedestrian Collisions*. Chinese Journal of Automotive Engineering, 2011.

[2] Lan F C, Cai Z H, Chen J Q, et al. *Biomechanical responses and injury evaluation of human thorax and abdomen during vehicle collision*. Huanan Ligong Daxue Xuebao/journal of South China University of Technology, 2012. **40**(12): p.70-78.

[3] Liu W, Hui Z, Li K, et al. *Study on pedestrian thorax injury in vehicle-to-pedestrian collisions using Finite Element Analysis*. Chinese Journal of Traumatology, 2015. **18**(2): p.74-80.

[4] Watanabe R, Katsuhara T, Miyazaki H, et al. *Research of the relationship of pedestrian injury to collision speed, car-type, impact location and pedestrian sizes using human FE model (THUMS Version 4)*. Stapp Car Crash Journal, 2012. **56**(9): p.269-321.

[5] Lv W, Shijie R, Li H, et al. *Injury Analysis of a Six-Year-Old Child Pedestrian Thorax in Lateral/Oblique Impact*. IEEE Computer Society, 2016: p.352-358.

[6] Moghaddam F R, Afandizadeh S, Ziyadi M. *Prediction of accident severity using artificial neural networks*. International Journal of Civil Engineering, 2011. **9**(1): p.41-49.

[7] Nilsson G. *Traffic safety dimensions and the power model to describe the effect of speed on safety*, 2004.

[8] Elvik R. *A re-parameterisation of the Power Model of the relationship between the speed of traffic and the number of accidents and accident victims*. Accident; analysis and prevention, 2013. **50**(2): p.854-860.

[9] Tefft B C. *Impact speed and a pedestrian's risk of severe injury or death*. Accident Analysis & Prevention, 2013. 50: p.871-878.

[10] Islam S, Mannering F. *Driver aging and its effect on male and female single-vehicle accident injuries: Some additional evidence*. Journal of Safety Research, 2006. **37**(3): p.267-276.

[11] Morgan A, Mannering F L. *The effects of road-surface conditions, age, and gender on driver-injury severities*. Accident; analysis and prevention, 2011. **43**(5): p.1852-63.

[12] Behnood A, Roshandeh A M, Mannering F L. *Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities*. Analytic Methods in Accident Research, 2014. **3–4**(3–4): p.56-91.

[13] Abu-Zidan F M, Eid H O. *Factors affecting injury severity of vehicle occupants following road traffic collisions*. Injury-international Journal of the Care of the Injured, 2015. **46**(1): p.136-41.

[14] Metter E J, Conwit R, Tobin J, et al. *Age-associated loss of power and strength in the upper extremities in women and men*. Journals of Gerontology, 1997. **52**(5): p.267-76.

[15] Li K, Fan X, Yin Z. *Pedestrian injury patterns and risk in minibus collisions in china*. Medical Science Monitor International Medical Journal of Experimental & Clinical Research, 2015. 21: p.727-34.

[16] Hongmin X U, Guo Z, Xiaoyu L I, et al. *Prediction on crossing accident based on BP neural network of optimized Genetic Algorithm*. Railway Computer Application, 2016.

[17] Tang Y S, Li-Na G E, Huang Z L, et al. *Study of Traffic Accident Prediction Method Based on BP Neural Network*. Journal of Liaoning University of Technology, 2016.

[18] Zhang Y H. *Application of BP Neural Network in Structural Damage Diagnosis of Bridge behind Abutment*. Applied Mechanics & Materials, 2016. 847: p.440-444.

[19] Jiang L, Zhang J, Xuan P, et al. *BP Neural Network Could Help Improve Pre-MiRNA Identification in Various Species*. Biomed Research International, 2016.

[20] Liu W J, Li K, Su S, et al. *Car-pedestrian accident reconstruction based on finite element simulation and genetic neural network*. Yiyong Shengwu Lixue/journal of Medical Biomechanics, 2015. **30**(2): p.125-130.

[21] Su S, Liu W J, Wang F P, et al. *Comparison of Different Means to Determine Postcrash Velocity in a Real-World Vehicle-Pedestrian Accident*. Applied Mechanics & Materials, 2014. 496-500: p.3031-3033.

[22] Njikam A N S, Zhao H. *A novel activation function for multilayer feed-forward neural networks*. Applied Intelligence, 2016: p. 1-8.

[23] Huang G, Huang G B, Song S, et al. *Trends in extreme learning machines: A review*. Neural Networks, 2015. 61: p.32-48.

[24] Hagiwara K, Fukumizu K. *Relation between weight size and degree of over-fitting in neural network regression*. Neural Networks, 2008. **21**(1): p.48-58.