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Evaluation of Stress Transfer Parameter from Pedicle Screw Parameters by Artificial Neural Network

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Abstract

The parameters of bone screw were the main effect to von Mises stress distribution on the screw that involved stress transfer to the surrounding bone. A dimensionless stress transfer parameter was an indicator ranking the performance of pedicle screw, was found by the ratio of stress distribution on the screw and the bone. Finite element analysis (FEA) was a popularly tool to analyze the stress distribution on the screw and the bone but it took for a long time. Artificial neural network (ANN) was an alternative method to solve the stress distribution on the bone-implant by learning data from finite element analysis, was used a short time to analyze. This research aims to use the artificial neural network to predict the stress transfer parameter. Transfer function and number of neurons were varied to analyze the best result of stress transfer parameter. From the result, the nonsymmetrical model was hardly to found the relationship that shown the statistical indicators as RMSE = 0.506 and MAPE = 15.096%.

Keywords: Artificial Neural Network, Pedicle Screw, Stress Transfer Parameter

1. Introduction

The pedicle screw was commonly used to insert the cervical spine to fix the fracture bone for a surgical treatment as shown in Fig. 1. The screw parameters affected the stress distribution on pedicle screw and surrounding bone. A dimensionless stress transfer parameters (STP) was an indicator to specify the performance of pedicle screw. There are two parameters related with STP: the first was α that defined by ratio of the stress distribution on the bone over the first thread of screw and the stress distribution on the first thread of screw. The second was β that define by ratio of the stress distribution on the bone under the first thread of screw and the stress distribution on the other threads excluding the first thread of screw.

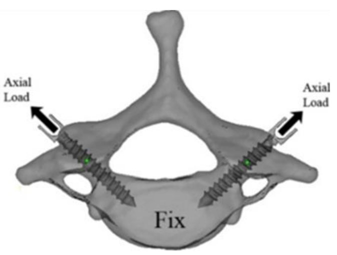

Fig. 1 The pedicle screw inserted cervical spine.

The three-dimensional models of cervical spines were constructed by reverse engineering method from computerized tomography (CT) data and the three-dimensional model of pedicle screws were created by SolidWorks software. The MSC program was used to analyze the stress distribution on pedicle screw was inserted cervical spine. The complex shape and boundary condition were took a long computational time and consumed more resource of the computer to analyze, therefore artificial neural network (ANN) could be used to solve the complex problem, which take a less time and computer's resource in analyzing process. The artificial neural network contain the three layer as input, hidden and output layer, which work like the human's brain that can be train or learn from the supervised data. ANN had received many inputs and transfers the data to the others neuron. Weight and bias on each neuron were defined randomly but have changed gradually on computation of iteration until the errors between target values and predicted values were minimized, was called backpropagation algorithm.

This research aims to use the artificial neural network to predict the stress transfer parameter. Transfer function and number of neurons were varied to analyze the best result of stress transfer parameter.

2. Material and Method

2.1 Stress-Transfer Parameter of Pedicle screw

The dimensionless stress transfer parameter had two parameters as shown in Eq. (1) and (2). The first was α that evaluated from the stress distribution on the first thread of screw to withstand an average stress on the bone over the first thread and the other one was β that evaluated from the stress distribution on the thread excluding the first thread to bear an average stress on the bone between these thread as shown in Fig. 2.

$$\alpha = \frac{\sigma_{fb}}{\sigma_{ft}} \qquad (1)$$

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$$\beta = \left(\frac{1}{N} \sum_{i=2}^{N} \sigma_{bi} \Big/ \frac{1}{N} \sum_{j=2}^{N} \sigma_{tj} \right) = \left(\sum_{i=2}^{N} \sigma_{bi} \Big/ \sum_{j=2}^{N} \sigma_{tj} \right) \quad (2)$$

A dimensionless STP could be applied to classify the different types of screw designs. Ideally, the STP will get closer to unity but in generally provided 0.96-0.99 [1] and commonly approach to be over 0.3 [2].

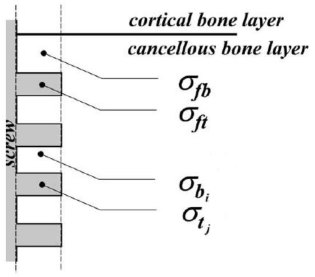

Fig. 2 The dimensionless STP components [2].

2.2 Input Array of Pedicle Screw Parameters

The screw parameters affected the STP were six variables as an input array including: outer diameter (OD), inner diameter (ID), thread width (TW), proximal root radius (PRR), distal root radius (DRR) and pitch (P) as shown in Fig. 3. The range of designing parameters were determined according to 4.9-7.5 mm for OD, 3.8-5.0 mm for ID, 0.1-0.3 mm for TW, 0.8-3.3 mm for PRR, 1.2-3.3 mm for DRR and 2.7-3.0 mm for P.

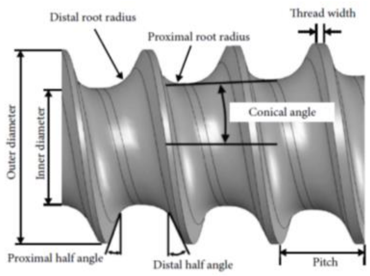

Fig. 3 The pedicle screw parameters [3].

The input array was normalized in a linear range from 0 to 1 as well as the initial weight and the biases were randomly chosen from -1 to 1 [4]. Input array, the entire 25 data were divided into three groups consist of 60% for training, 20% for validation and 20% for testing. Generally, the satisfied model of artificial neural network was obtained after completely training the model and the model could be used to test sample set. In this study, 10 quantities of sample set were applied by randomly selected screw parameters.

2.3 Artificial Neural Networks Modeling

Artificial neural network was a computational method inspired from biological neural processing of human’s brain. Neural network consist of three main layers as input layer, hidden layer and output layer. Each layer contains many neurons and connectors with biases and weights of each specific neuron as shown in Fig. 4.

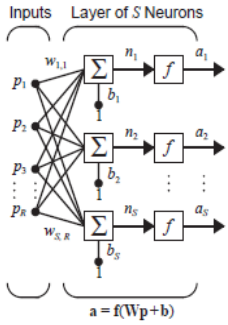

Fig. 4 Architecture of neuron network [4].

The modeling of artificial neural network was adopted a multilayer feedforward and error-backpropagation as shown in Fig. 5 with sigmoid activated function through layer to layer and was used log-sigmoid (logsig) and hyperbolic tangent sigmoid (tansig) transfer function in hidden layer also linear (purelin) transfer function in output layer. Levenberg-Marquardt backpropagation algorithm (trainlm) was applied to train the neural network for solving the non-linear least square systems. The learning rate was a factor that affects the learning algorithm and capability to converge the achieving rate. When the learning rate was too large, the searching path will meet the goal slowly because of swirling around the target. Contrarily, learning rate was too small searching path gradually approaches the goal causing increase the total time. The momentum coefficient was the weight to encourage movement as the same way. When the momentum coefficient was too large, it could help increase the speed to achieve the goal nevertheless it might be in risk of overshooting minimum. On the other hand, momentum coefficient is too small that increase the total time as well [5, 6]. Choosing learning rate and momentum coefficient was 0.5 of both values, so the new bias and weight value of each epoch had changed as errors between forecast and desire value, which are gradually minimizing on computation of iteration. The processing iteration was terminated when the errors were small.

In this study, the activated functions log-sigmoid and hyperbolic tangent sigmoid was varied while the linear function was fixed. The numbers of neurons in hidden layer were varied and the numbers of neurons in input and output layer were fixed as shown in Table. 1. There are six models were used to analyze on MATLAB program.

Table. 1 Varied transfer functions and number of neurons on training conditions.

Model	Neurons (Input-Hidden-Output)	Activated functions	Training function
1	6-3-1	Logsig - Purelin	Trainlm
2	6-3-1	Tansig - Purelin	Trainlm
3	6-6-1	Logsig - Purelin	Trainlm
4	6-6-1	Tansig - Purelin	Trainlm
5	6-12-1	Logsig - Purelin	Trainlm
6	6-12-1	Tansig - Purelin	Trainlm

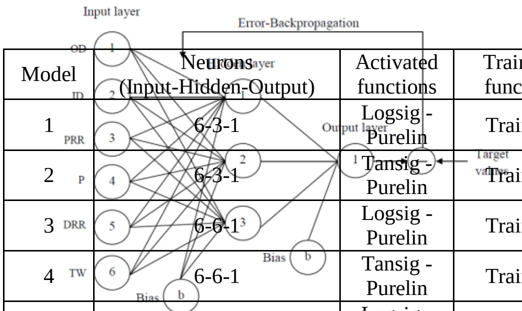

Fig. 5 The three layers artificial neural network.

2.4 Statistical forecasting neural network

The artificial neural network performances of testing network were evaluated by several statistic indicators, compared between actual and predict values, commonly using coefficient of determination (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE). The coefficient was used to judge the trend between target and observed variables, which closer to one for a good value. The root mean square error and mean absolute percentage error were defined as difference between desired values and predicted values, which closer to minimum for a good value [7]. The equations, was represented the statistical indicators was shown in Eq. (3) for RMSE and Eq. (4) for MAPE respectively.

Root mean square error (RMSE):

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(P_i - A_i\right)^2} \tag{3}$$

Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_i - A_i\right|}{A_i}x100\% \tag{4}$$

Where:
A_i were actual value for the ith from neural network.
P_i were predict value for the ith from neural network.
N was the number of testing sample.

3. Result and Discussion

According to artificial neural network analyzed and mapped pedicle screw parameters against the dimensionless stress-transfer parameter. The neural network was varied the number of neurons and the activated functions to significantly investigate an effect of parameters. Six models were considered to find the best performance of neural network. The best prediction result in each case was chosen from statistic indicators. The output after training and testing had been completed which a result brings minimized error as shown in Table. 2.

Table. 2 The statistical results of STP by artificial neural network.

Model	Activated functions		Number of neurons		R^2	RMSE (STP)	MAPE
	Hidden layer	Output layer	Hidden layer	Output layer			
1	Logsig	Purelin	3	1	0.506	0.068	15.096%
2	Tansig	Purelin	3	1	0.475	0.071	16.925%
3	Logsig	Purelin	6	1	0.492	0.069	15.336%
4	Tansig	Purelin	6	1	0.440	0.073	15.972%
5	Logsig	Purelin	12	1	0.497	0.068	15.721%
6	Tansig	Purelin	12	1	0.466	0.073	15.467%

After the algorithm has been done the lowest value of root mean square error (RMSE) and mean absolute percentage error (MAPE) occurred at the first model, which was used activated function as logsig-purelin and 3 neurons in hidden layer as shown in Fig. 6. The coefficient of determination (R^2) between two variables should be close to 1 for a good network relationship prediction.

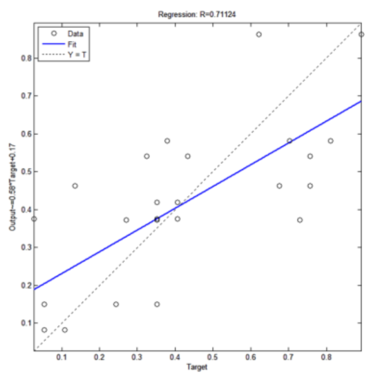

Fig. 6 Regression plot of the first model.

The performance of neural network was identified from the good answer after simulation. Two keys forward to achieve a goal value were shown in Fig. 7 as follows: First, the validation line (green line) and the test line (red line) should be a parallel or tend to be the same style. The second, the train line (blue line) should decrease continuously or be down until steady. The vertical dashed line was represented the best epoch and horizontal dashed line show a goal of minimized error in each iteration [8-9].

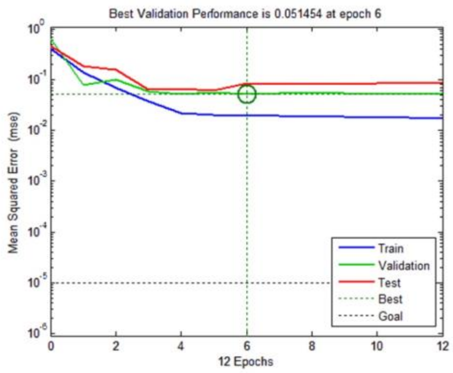

Fig. 7 Performance plot of the first model.

The six models of artificial neural network successfully use to predict the dimensionless stress-transfer parameter, was completely met a less errors. Considering the STP, the first model log-sigmoid transfer function gave the lowest errors compared with the other log-sigmoid model and produced the highest coefficient of determination. Nevertheless, the statistical indicators provided to consider the ranking accuracy of neural network.

From previous research, the three-dimensional model was created from SolidWorks software with symmetrical shape was used to calculate the stress distribution on the model by finite element analysis to analyze the STP but the artificial neural network was simply to predict the STP with less time and computer's resource than finite element method because the symmetrical model and the pedicle screw parameters have a good relationship [10]. In case of bone model from computerized tomography data with the unsymmetrical shape, the neural network was arduous matching the unsymmetrical model because of the complication of actual bone shape. A method to improve the result is using the genetic algorithm to optimal the screw parameters with an evolutionary algorithm.

4. Conclusion

Artificial neural network was an engineering tool to forecast the stress transfer parameter based on finite element analysis but the complication of unsymmetrical shape bone model was hardly to evaluate the input array and target value relationship. The evolutionary algorithm is going to be considered to improve the problems for easy making new screw design from pinpoint solution of STP [11-12].

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