SHEAR STRESS IN ARTERIES WITH MYOCARDIAL BRIDGE PREDICTED WITH NEURAL NETWORKS

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Abstract:

Coronary arteries and their branches, which supply nutrient and oxygenated filled blood to the (myocardium), heart muscle lie on the surface of the heart, in the subepicardial space, between the visceral pericardium (epicardium) and myocardium. In some cases, a shorter or longer segment of the epicardial coronary artery or its branch is covered by a band of the heart muscle that lies on top of it. This intramural segment of the coronary artery is called a "tunneled artery" and the band of muscle is called a "bridge". MB (myocardial bridging) is a congenital coronary anomaly and it is defined as a segment of a major epicardial coronary artery that runs through the myocardium beneath the muscle bridge. It`s very important to find the most efficient method for determining shear stress inside of the coronary arteries with a myocardial bridge. This article describes the procedure for calculating the shear stress of MB arteries using a neural network trained with the results of the finite element method.

Keywords: Myocardial bridging, wall shear stress, coronary artery, neural network.

1. Introduction

The value of arterial shear stress using Myocardial Bridge (MB) is very important for a physician. Low shear stress (<1.5 N/m2) can lead to vasoactive agents such as growth-promoting and thrombus-promoting phenotypes and they can eventually result in atherosclerosis. Acquiring a predisposition to sclerosis [1, 3, 4, 5]. On the other hand, normal shear stresses with a positive time average in the range of 1.5 N/m2 to 7.0N/m2 increase nitric oxide (NO) production in endothelial cells and atheroma associated with the standing effect of atheroma protectants. It down-regulates the expression of developmental promoters [12,13,14]. In addition, SEM (scanning electron microscope) shows that the shape of the endothelial cells in the LAD intima changes from a flat, polygonal segment proximal to the MB, to a spiral spindle below the MB. [2, 6, 7]. Since it is not possible to measure the shear stress of the myocardial bridge artery, it is very important to find a way to calculate this value. One of the most effective methods is the FEM (Finite Element Method). This is a very complex and slow mesh generation and resolution process that requires very high computational power, so it is desirale to find a fast and simple method that can be used, and the solution proposed in this paper is Neural network.

2. Methods and materials

2.1 FE model Artery with MB

FE models of arteries using MB are created with finite element modeling and meshing software. After creating the mesh, the application will automatically run the FE solver, wait for the results, import the results and create a neural network training file. The block diagram of the application is shown in (Figure 1). [13].

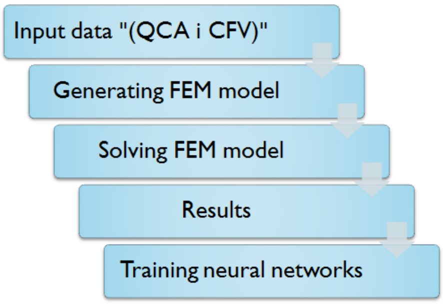

Fig. 1. Block diagram

Although CT image segmentation is the best way to create the shape of a particular organ, MB is a very rare disease and is detected by angiography in amedical setting. For this reason, software has been developed and it generates geometry from QCA measurement data from angiographic images. The software automatically creates four different meshes for each cardiac cycle measurement period. Based on these four meshes, the software interpolates the shape of the mesh model throughout the cardiac cycle. The movement of the mesh is important for the accurate calculation of blood flow through the MB.

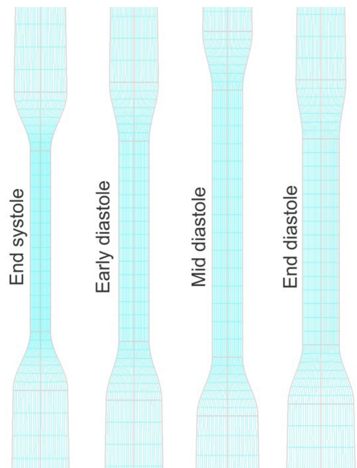

Fig. 2. Generated FE 2D model meshes during fourperiods of a heart cycle

2.2 Neural network model

The results of the FEM model are used for training the neural networks. In this study, calculations were performed on 12 different patients with MB. Training a neural network required a large number of patients.

For these purposes, the input data for 2000 patients was randomly generated based on data from real patients with a 30% variance. The graph structure of the neural network used to predict the shear stress of the artery using MB is shown in Figure 3)

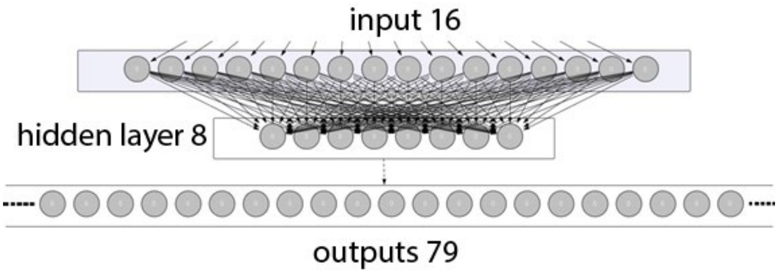

Fig. 3. Graphical representation of the neural network

The software package MATLAB was used in order to generate and train the neural network.

The problems that are a part of the traditional form of backpropagation algorithms are problems of local minima and slow convergence. Many variations of this algorithm have been developed to overcome these problems [13]. We used a multi-layer perceptron neural network to predict WSS, REST, and OSI. This network was trained using a backpropagation algorithm. The adaptation of weight coefficient:

$$w_{i,j(l)}(t+1) = w_{i,j(l)}(t) + \Delta w_{i,j(l)}(t+1)$$
$$w_{i,j(l)}(t+1) = \eta\alpha \frac{\partial E_k}{\partial w_{i,j(l)}} + \alpha \Delta w_{i,j(l)}(t) \quad (1)$$

The learning speed η in equation (1) is variable. As the reference function decreases as it reaches the goal at each epoch, the learning rate increases with a coefficient of η_{inc}. Table 1 shows the values of the parameters α, η_{inc}, η_{dec} and max_{inc} used to solve the problem.

α	η_{inc}	η_{dec}	max_{inc}
0.9	1.05	0.7	1.04

Table 1. RMSE values

The criterion for learning stopping is defined as 3000 epochs.

3. Results

The technique and the calculation of relative mean squared error - RMSE - were used to test the neural network:

$$RMSE = \frac{\sum_{i=1}^{N}\sum_{j=1}^{S}(y_i(j) - \widehat{y}_i(j))^2}{\sum_{i=1}^{N}\sum_{j=1}^{S}(y_i(j) - \overline{y}(j))^2} \quad (2)$$

where N represents the total number of examples (3000), s represents the total number of outputs (79), is the real value of the j-th output, i-th example, is the mean value of the j-th output, and is the neural network prediction of the j-th output, i-th example.

Table 2 shows the RMSE values derived from neural network testing.

Model	RMSE
WSS	0.096

Table 2. RMSE values

A RMSE score less than 1.0 indicates that the model is usable (it has less errors than a non-intelligent model) [14]. Table 2 shows that the neural network has a lot of potential for predicting WSS.

4. Conclusions

The advantage of neural networks is that they produce very precise answers in just a few seconds after being trained based on multiple input factors and this is critical in clinical practice. However, the most significant disadvantage is that we must employ results already obtained from methods such as the finite element approach provided with several simulations in order to train the network. Theprocedure of preparing the results for neural network training is very slow, and it takes a lot of computational power to solve all of the FEM models, as well as a trained individual who is familiar with the FEM method.

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