Cardiac and Cardiovascular Research (2021) Volume 2 Issue 1, *8 pages*.
doi: 10.54517/ccr.v2i1.1894

ORIGINAL RESEARCH ARTICLE

Research on inversion method of left ventricular myocardial tissue parameters based on BP neural network

Qishuai Zhang[1], Kehu Yang[2], Luxian Li[1*]

*[*1] Shaanxi Key Laboratory of Environment and Control for Flight Vehicle, State Key Laboratory for Strength and Vibration of Mechanical Structures, School of Aerospace Engineering, Xi'an Jiaotong University, Xi'an 710049, Shaanxi, China. E-mail: luxianli@mail.xjtu.edu.cn*

[2] State Key Laboratory of Integrated Service Networks, School of Telecommunications, Xidian University, Xi'an 710000, Shaanxi, China.

ABSTRACT

Because it contains pathological characteristics such as changes in myocardial tissue characteristics, the deformation and dynamic characteristics of human left ventricle have become an important basis for clinical diagnosis of heart disease. Based on BP neural network method, this study carries out the identification of left ventricular myocardial tissue parameters through the inversion of left ventricular clinical diagnosis data. Firstly, the image recognition program is written in MATLAB language to extract the location points of inner and outer membranes in human left ventricular CT image, establish the real geometric model of left ventricle in solidworks software, and establish the finite element analysis model of left ventricle through ABAQUS software. Secondly, Mooney Rivlin hyperelastic model is used to simulate the characteristics of myocardial tissue, ABAQUS finite element software is used to conduct dynamic numerical analysis on the left ventricular finite element model, and 45 groups of input target vectors of BP neural network corresponding to three characteristic moments are obtained. Finally, the BP neural network program is written in MATLAB language to train the input target vector, and establish the nonlinear mapping relationship between left ventricular diagnostic data and myocardial tissue parameters. The analysis results of examples show that BP neural network can be well used for myocardial tissue parameter inversion based on clinical data, and is expected to become an effective method for clinical diagnosis of left ventricular lesions caused by changes in myocardial tissue characteristics.

Keywords: left ventricle; finite element modeling and analysis; mooney-rivlin model; deformation analysis; bp neural network; inversion of myocardial tissue parameters

1. Introduction

In recent years, with the deepening of cardiac mechanics research, the tissue characteristics of human myocardium have gradually become an important indicator of heart health[12]. Research shows that compared with healthy people, the

ARTICLE INFO
Received: February 10, 2021 | Accepted: March 20, 2021 | Available online: April 7, 2021

CITATION
Zhang Q, Yang K, Li L. Research on inversion method of left ventricular myocardial tissue parameters based on BP neural network. Cardiac and Cardiovascular Research 2021; 2(1): 8 pages.

myocardial hardness of patients with diastolic heart failure or myocardial infarction is much higher [35]. Therefore, the study of myocardial tissue characteristics is of great significance for the clinical diagnosis of heart disease.

Limited to the difficulty of obtaining human myocardial tissue specimens [67], the researchers mainly rely on animal experimental models to study the characteristics of myocardial tissue, that is, assuming that the characteristics of myocardial tissue conform to a specific constitutive relationship, obtain the stress-strain curve through uniaxial tensile, biaxial tensile or shear tests of specimens, and determine the material parameters in the constitutive equation.[810] Although this method can quantitatively analyze the tissue characteristics of myocardium, there is an obvious difference between the measured results of isolated inactivated myocardium and the real myocardial characteristics with blood flow characteristics [3]. In addition, there are differences between animal myocardial tissue and human myocardial tissue, and the referentiality of the results has been controversial.[5]

In view of the difficulties in obtaining the characteristics of myocardial tissue, this study proposes an inversion method based on intelligent optimization algorithm. The BP (back propagation) neural network structure of parameter inversion is established by using left ventricular dynamic response data to map the nonlinear relationship between left ventricular dynamic response and myocardial tissue parameters. Input the clinical non-invasive left ventricular diagnostic data of individual patients into the trained BP neural network to inverse the myocardial tissue parameters of the tester. The inversion method based on BP neural network can not only obtain the characteristics of myocardial tissue, but also meet the rapid time response requirements of clinical heart disease detection.

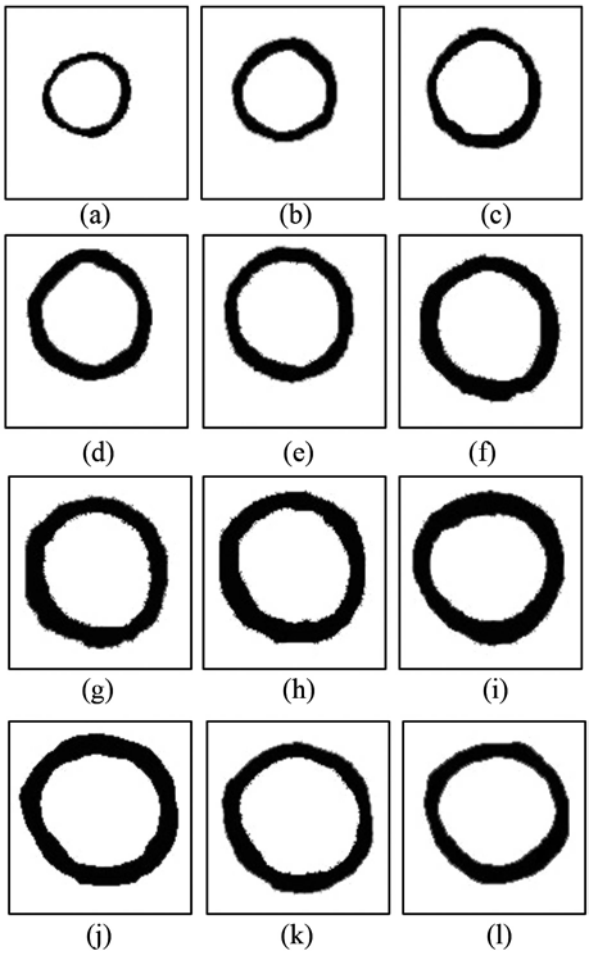


Figure 1. CT Image of LV sections.

2. Finite element modeling of left ventricle

2.1. Geometric model of left ventricle

The geometric model in this study comes from the CT scanning data of the inner and outer membrane of the human left ventricle (LV). First, perform equally spaced (5mm) scanning along the left ventricular axis to obtain 12 left ventricular CT images of different sections, as shown in **Figure 1** (a) -(L).

Then, the image recognition program is written in MATLAB language to extract the location points of left ventricular epicardium in CT image, as shown in **Figure 2** (a) and (b).

Further, the geometric model of left ventricle is established through solidworks software, as shown

in **Figure 3**.

2.2. Finite element model of left ventricle

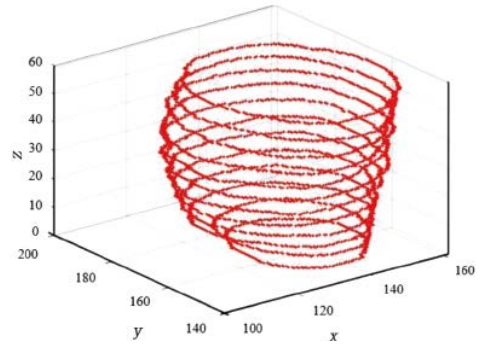
After calculating the CT images of 12 different sections in **Figure 1**, the average thickness of left ventricular myocardium is 5.65mm, and the average thickness of 8 sections in layers 5~12 is about 6mm. Based on the geometric model of the left ventricle in **Figure 3**, the middle surface is extracted to form the shell structure of the left ventricle, and 6mm is taken as the thickness of the shell. Using the automatic meshing function of ABAQUS software to control the boundary seed density and mesh attributes of the left ventricular model, the shell structure finite element mesh shown in **Figure 4** is obtained, with a total of 4084 S4R shell elements and 60 s3r shell elements, and a total of 4150 nodes.

3. Establishment method of BP inversion data

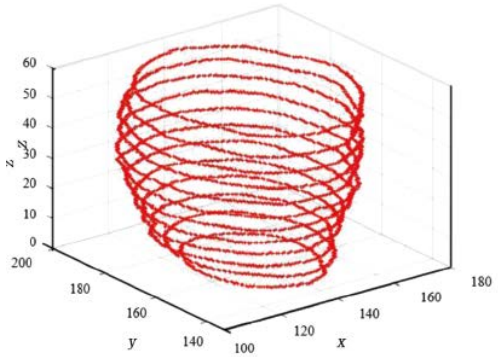
BP neural network can map any complex nonlinear function relationship[11,12]. In this study, BP neural network technology is used to retrieve the performance parameters of myocardial tissue. Therefore, we first conduct dynamic finite element analysis on the left ventricle to obtain the training data of BP neural network.

3.1. Myocardial tissue characteristics

Human myocardium is a super elastic and incompressible natural biomaterial with specific properties. Based on the different characteristics of myocardial performance, many scholars have established the description method of myocardial tissue performance, but so far there is still no widely recognized expression form. This study focuses on the research of inversion method, which regards the myocardium as isotropic hyperelastic material. For the actual anisotropic myocardial tissue, this research method will still be applicable after increasing the number of parameters and the amount of inversion calculation.



(a) Intima



(b) Adventitia

Figure 2. The LV CT Data recognized by Matlab.

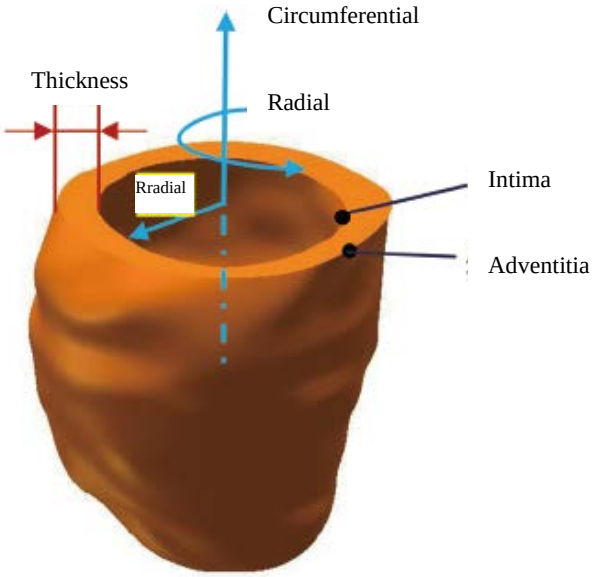


Figure 3. CT image based geometric model of the LV.

Figure 4. Finite element model of the LV.

For isotropic hyperelastic materials, we select the most commonly used incompressible Mooney Rivlin model [13], and the expression of its energy density function is:

$$W = C_{10}(\tilde{I}_1 - 3) + C_{01}(\tilde{I}_2 - 3) \quad (1)$$

Where W is the strain energy density function, $\tilde{I}_1$ and $\tilde{I}_2$ are the first and second invariants of deformation tensor bias, and C_{10} and C_{01} 1 are the two performance parameters of myocardial tissue.

3.2. Load analysis

The periodic contraction and expansion of the heart come from two factors, one is the active force generated by the cardiac muscle stimulated by ECG, and the other is the passive force generated by the reaction of heart deformation by internal blood pressure[14]. The active force can be through myocardial excitation σ. The change with excitation time t is expressed as [14]:

$$\sigma = \begin{cases} \sigma_{\max}\sin\left(\frac{t-\tau}{T_e}\pi\right), 0 \leqslant t \leqslant T_e \\ 0, t > T_e \end{cases} \quad (2)$$

Among τ Is the propagation sequence at different times, T_e is the excitation cycle, σ_{max} works hard for the muscle bar. This study takes the same parameters as literature [15], i.e σ_{max} = 53.3 kpa and T_e= 0.353 s. Excitation sequence τ It is generally difficult to determine [15], which is taken as 0 in this study. The left ventricle is powered indirectly by arterial pressure[7,15]. The load change of left ventricle in a cardiac cycle is shown in **Figure 5**.

3.3. Acquisition of BP input data

Given the myocardial tissue parameters (i.e. The target vector of BP neural network), the fixation constraint is applied to the heart bottom position of the left ventricular finite element model, and the evenly distributed radial passive force and circumferential active force in **Figure 5** are applied to the inner and outer surfaces respectively. The deformation process of the left ventricle within 0.8 s of a cardiac cycle is analyzed by using the explicit solver of ABAQUS software[15], and the deformation process shown in **Figure 6** is obtained. It can be seen that at different times in a cardiac cycle, the left ventricle has obvious systolic deformation, which is very similar to the real left ventricular movement process.

Through the finite element analysis of the left ventricle, the deformation of any position of the left ventricle can also be obtained. In this study, four typical cross-sectional positions of left ventricle z = 8, 20, 32 and 44mm (see **Figure 7**) are selected, and the radial displacement value at some time in the cardiac cycle is used as the input vector of BP neural grid.

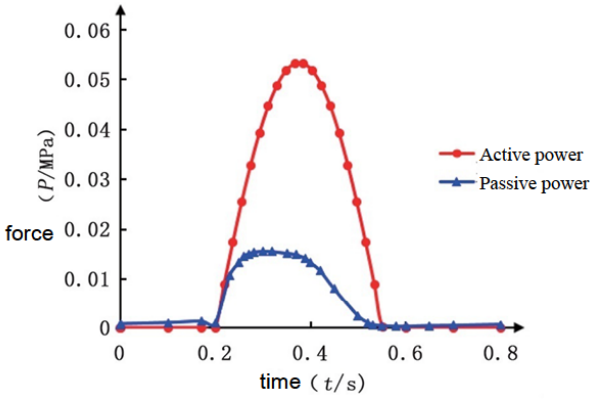


Figure 5. Variation of loading with time for the LV[15-16].

(a) t=0.2s (initial contraction) (b) t= 0.4s (mid-systolic) (c) t=0.6s (end-systolic)

Figure 6. Geometric variation of the LV during a period of contraction.

4. Inversion of myocardial tissue parameters based on BP neural network

4.1. Basic idea of 1bp neural grid inversion

BP neural network is a multilayer feedforward network trained by error back propagation algorithm. It is one of the most widely used neural network models [17] BP neural network is composed of input layer, hidden layer and output layer. Without limiting the nodes of hidden layer, the three-layer neural network can approach any nonlinear function relationship in theory [18], as shown in **Figure 8**.

Parameter inversion based on BP neural network is to establish the nonlinear relationship between response and parameters, including the following basic steps[19]:

(1) Determine the value range of parameters to be inversed;

(2) Evenly disperse the values within the parameter range to obtain the target vector;

(3) Obtain the input vector through the response;

(4) Input the input and target vectors into BP neural network for training;

(5) Using the mapping relationship between input and output of BP neural network, the human left ventricular diagnostic data is input into the neural network inversion parameters.

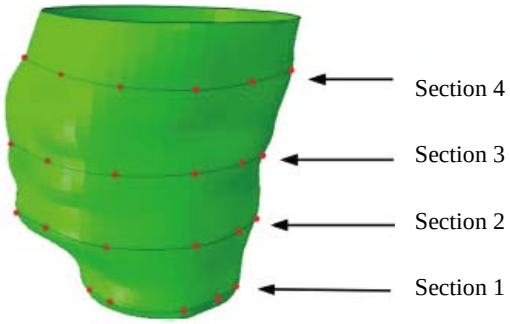


Figure 7. Distribution of sampling points in LV structure.

The above five steps can be summarized as the establishment of BP neural network (including steps (1)-(4)) and parameter inversion (i.e. Step (5)), which will be studied separately below.

4.2. Establishment of BP neural network

(1) Establishment of input vector and target vector according to literature [20], the normal left ventricular myocardial tissue parameters represented by Mooney Rivlin model are C10 = 0.178 mpa and C01 = 3.989 mpa respectively, and the density is 1.370×103 kg/m3. Accordingly, the possible value ranges are determined as 0.100 ≤C10 ≤0.300 and 3.000 ≤C01 ≤5.000; Based on the orthogonal experimental design method, the two parameters are combined, taking C10 = 0.100, 0.150, 0.200, 0.250, 0.300, C01 = 3.000, 3.250, 3.500, 3.750, 4.000, 4.250, 4.500, 4.750, 5.000 as the target vector of BP neural network training.

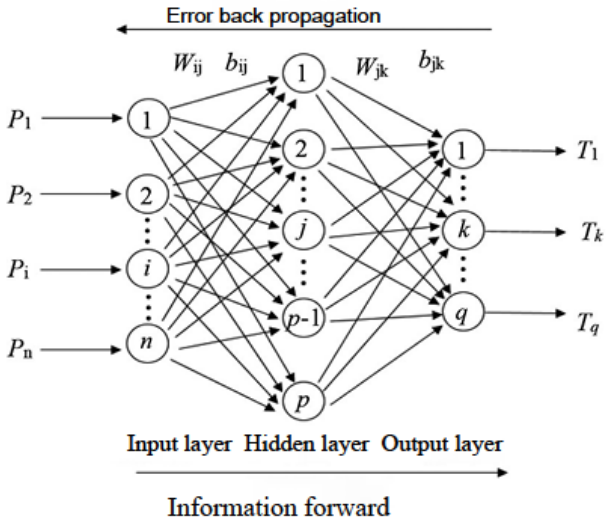


Figure 8. The topologic structure of BP neural network.

The radial displacement on four typical sections of the left ventricle at three characteristic times of t = 0.2 s (initial systole), t = 0.4 s (middle systole) and t = 0.6 s (end systole) in the cardiac cycle is taken as the input vector of BP neural network. Take 12 points at equal intervals on each section, a total of 48 points. The left ventricular model under different myocardial tissue parameters corresponds to different radial displacement, forming 45 groups of training samples. Under three characteristic moments, 45 groups of training samples at corresponding moments are obtained, as shown in **Table 1**, **Table 2** and **Table 3** respectively.

Table 1. Radial displacements at the LV from different myocardial tissue parameters (at t = 0.2 s)

Number of layers	Serial number	Circumferential position (mm)	Group 1	Group 2	…	Group 20	…	Group 45
1st floor	1	0.00	0.036	0.052	…	0.050	…	0.035
	2	9.22	0.048	0.048	…	0.048	…	0.037
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	12	86.98	0.035	0.053	…	0.051	…	0.035
⋮	⋮	⋮	⋮	⋮		⋮	⋮	⋮
4th floor	1	0.00	0.051	0.071	…	0.068	…	0.046
	2	30.96	0.077	0.098	…	0.096	…	0.092
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	12	172.52	0.046	0.066	…	0.063	…	0.043

Table 2. Radial displacements at the LV from different myocardial tissue parameters (at t =0.4 s)

Number of layers	Serial number	Circumferential position (mm)	Group 1	Group 2	…	Group 20	…	Group 45
1st floor	1	0.00	3.180	4.162	…	3.961	…	2.968
	2	9.22	3.098	4.093	…	3.891	…	2.876
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	12	86.98	3.123	4.091	…	3.892		2.916
⋮	⋮	⋮	⋮	⋮		⋮	⋮	⋮
4th floor	1	0.00	0.665	0.863	…	0.827		0.612
	2	30.96	0.638	0.845	…	0.806		0.585
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	12	172.52	0.610	0.790	…	0.757	…	0.561

(2) The selection of hidden layer and activation function hidden layer is determined according to experience and many experiments. In this study, the number of input units is 48 and the number of output units is 2. The range of the number of hidden layer units calculated according to the empirical formula is [7,18]. Then the samples are trained by BP neural algorithm, and the optimal number of hidden layer units is determined to be 15 by comprehensively considering the error during convergence and the number of iterations.

The hyperbolic tangent Tansig function is used for the activation function of the input layer and the hidden layer, the purelin linear function is used for the output layer, and the negative gradient descending momentum BP algorithm is used for the training function Next, use MATLAB software to compile and run the BP neural network program to obtain the BP neural network structure of myocardial parameter inversion, as shown in **Figure 9**.

Table 3. Radial displacements at the LV from different myocardial tissue parameters (at t =0.6 s)

Number of layers	Serial number	Circumferential position (mm)	Group 1	Group 2	…	Group 20	…	Group 45
1st floor	1	0.00	-0.586	-2.604	…	-2.398	…	-0.179
	2	9.22	-0.557	-2.383	…	-2.204	…	-0.178
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

	12	86.98	-0.571	-2.517	…	-2.320	…	-0.173
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	1	0.00	-0.155	-0.523	…	-0.481	…	-0.070
4th floor	2	30.96	-0.163	-0.522	…	-0.489	…	-0.078
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	12	172.52	-0.140	-0.469	…	-0.430	…	-0.062

4.3. Inversion results and discussion of myocardial parameters

Clinically, the radial displacement of myocardium at different positions can be obtained through the left ventricular marker point method, so in order to verify this research method, it is assumed that the performance parameters of myocardial tissue are known. Based on this, the response data of left ventricular structure is obtained through finite element analysis, and then the size of myocardial tissue parameters is obtained through the inversion of response data through BP neural network, and the error is compared with the assumed myocardial tissue parameters. Through the inversion of myocardial tissue parameters of four hypothetical examples, the average value of inversion parameters at three characteristic times is obtained. **Table 4** shows the error between the average value of inversion parameters and the real value.

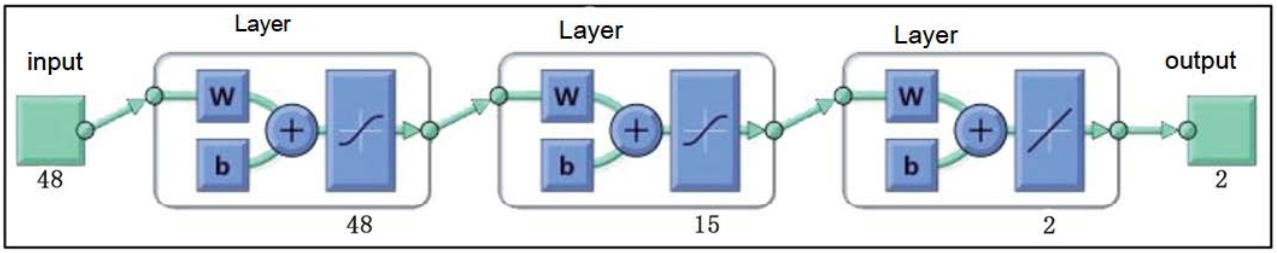


Figure 9. BP neural network model developed via Matlab software.

It can be seen from **Table 4** that the error between the average value of the inversion value and the real value of the four examples is within 3.58%, and the overall L2 norm relative error is 0.72%. Compared with the common error [21] in the process of clinical medical diagnosis, the inversion accuracy of the parameters in this study is higher, which can meet the requirements of clinical diagnosis. At the same time, it shows that the BP neural network established in this study has high reliability.

Table 4. The inversed results and their errors

Serial number	C_{10}			C_{01}		
	Average value of inversion value	real value	Error	Average value of inversion value	real value	Error
Group 1	0.192	0.190	1.12%	4.745	4.750	0.10%
Group 2	0.207	0.200	3.58%	4.264	4.300	0.85%
Group 3	0.149	0.150	0.89%	3.684	3.700	0.43%
Group 4	0.161	0.160	0.65%	3.358	3.400	1.24%
L2 norm relative error			0.72%			

5. Conclusions

Based on clinical CT images, the real three-dimensional geometric model of left ventricle was established; According to the dynamic finite element analysis results of the left ventricle, the inversion method of left ventricular myocardial tissue parameters based on BP neural network is proposed, and the myocardial tissue parameters under the Mooney Rivlin hyperelastic model of myocardial tissue are obtained. The average value of the inversion value is in good agreement with the real value, which proves the correctness of the inversion method of myocardial tissue parameters in this study

and provides an effective method for the accurate acquisition of human myocardial tissue performance.

The deformation data of left ventricular marker points obtained in clinic are input into the BP neural network trained in this study, and the myocardial tissue parameters are retrieved, which can be used as the basis for clinical heart disease diagnosis. The BP neural network algorithm in this study establishes a quantitative relationship between the left ventricular image and the intrinsic characteristics of myocardial tissue, which can quantitatively describe the health degree of the heart, thus providing a feasible way for the efficient and accurate diagnosis of clinical heart diseases.

Conflict of interest

The authors declare no conflict of interest.

References

1. Gao H, Li W G, Cai L, et al. Parameter estimation in a Holzapfel Ogden law for healthy myocardium. Journal of Engineering Mathematics 2015; 95(1): 231–248.
2. Davies V, Noè U, Lazarus A, et al. Fast parameter inference in a biomechanical model of the left ventricle by using statistical emulation. Journal of the Royal Statistical Society: Series C (Applied Statistics) 2019; 68(5): 1555–1576.
3. Chabiniok R, Wang V Y, Hadjicharalambous M, et al. Multiphysics and multiscale modelling, data model fusion and integration of organ physiology in the clinic: Ventricular cardiac mechanics. Interface Focus 2016; 6(2): 2015–2033.
4. Gao H, Aderhold A, Mangion K, et al. Changes and classification in myocardial contractile function in the left ventricle following acute myocardial infarction. Journal of the Royal Society, Interface 2017; 14(132): 2017–2023.
5. Hadjicharalambous M, Asner L, Chabiniok R, et al. Non invasive model based assessment of passive left ventricular myocardial stiffness in healthy subjects and in patients with non ischemic dilated cardiomyopathy. Annals of Biomedical Engineering 2017; 45(3): 605–618.
6. Nasopoulou A, Shetty A, Lee J, et al. Improved identifiability of myocardial material parameters by an energy based cost function. Biomechanics and Modeling in Mechanobiology 2017; 16(3): 971–988.
7. Fan L L, Yao J, Yang C, et al. Material stiffness parameters as potential predictors of presence of left ventricle myocardial infarction: 3D echo based computational modeling study. Journal of Medical Biomechanics 2015; 30: 82–83.
8. Sommer G, Haspinger D C, Andr□ M, et al. Quantification of shear deformations and corresponding stresses in the biaxially tested human myocardium. Annals of Biomedical Engineering 2015; 43 (10): 2334–2348.
9. Guan D B, Ahmad F, Theobald P, et al. On the AIC based model reduction for the general Holzapfel Ogden myocardial constitutive law. Biomechanics and Modeling in Mechanobiology 2019; 18(4): 1213–1232.
10. Sommer G, Schriefl A J, Andr□ M, et al. Biomechanical properties and microstructure of human ventricular myocardium. Acta Biomaterialia 2015; 24: 172–192.
11. Mi Baohong, Hong Wenxue, Song Jialin, et al. Research on the pre-diagnosis method of myocardial ischemia based on infrared thermal imaging technology and BP neural network. Advances in Lasers and Optoelectronics 2019; 56(1): 160–166.
12. Gao Yubo, Zhang Wei, Li Dacheng, et al. Inversion analysis of ceramic damage parameters based on back-propagation neural network. Journal of Ordnance Engineering 2018; 39(1): 146–152.
13. Xu Yu. Heart mechanics simulation based on finite element method [PhD thesis]. Harbin Institute of Technology; 2015.
14. Wu Guohua, Liu Feng, Xia Ling, et al. Establishment of finite element mechanical model of human left ventricular composite material. Chinese Journal of Biomedical Engineering 2002; 21(5): 404–410.
15. Nikou A, Dorsey S M, McGarvey J R, et al. Computational modeling of healthy myocardium in diastole. Annals of Biomedical Engineering 2016; 44(4): 980–992.
16. Wang Q J, Lu P. Research on application of artificial intelligence in computer network technology. International Journal of Pattern Recognition and Artificial Intelligence 2019; 33(5): 195–215.
17. He Y, Meng Z Y, Xu H, et al. A dynamic model of evaluating differential automatic method for solving plane problems based on BP neural network algorithm. Physica A: Statistical Mechanics and Its Applications 2020; 556: 124–145.
18. Li G, Hu Y, Li Q B, et al. Inversion method of in situ stress and rock damage characteristics in dam site using neural network and numerical simulation—A case study. IEEE Access 2020; 8: 46701–46712.
19. Tian Liang, Fan Qingming, Cao Yan, et al. Simulation of heart mathematical model based on hyperelastic materials. Rubber Industry 2019; 66(8): 577–580.
20. Fu Caofei. Cone beam CT-guided pelvic tumors in different fixed positions on a six-dimensional bed and the placement error of the target area. Medical Equipment 2020; 33(19): 12–20.