ATHEROMA PLAQUE VULNERABILITY PREDICTION USING MACHINE LEARNING TECHNIQUES

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Summary Nowadays clinical procedures for detection of vulnerable plaques are only performed by image analysis. The use of finite elements computations presents the disadvantage of very high computational cost when an immediate response is required. Our ultimate goal is to develop a quantitative method using Machine Learning Techniques for cumulative risk assessment of vulnerable patients based on atheroma plaque morphology which could replace the time consuming biomechanical simulations used in cardiovascular mechanics.

INTRODUCTION

Cardiovascular diseases related to atherosclerosis are the first cause of death in the western world; more people die annually from cardiovascular diseases than from any other cause. This relevant fact has motivated the development of numerical models for arterial behavior in order to understand better cardiovascular pathologies. The use of finite element methods (FEM) for the analysis and design of bioengineering processes often requires long computational time cost, the simulation time can be significantly reduced combining this technique with machine learning techniques.

The main objective of this work is to search for alternatives to direct FEM simulations in a specific clinical field, detection of vulnerable plaques, when an instantaneous response is needed. Thus, this work focuses on the uses of different machine learning techniques, such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), applied to the study the role of stress in plaque vulnerability in order to reduce the very long computation times and memory consumption required for 3D FE analysis.

The machine learning techniques use an intelligent algorithm to model the atheroma plaque rupture in terms of four of the most influential geometrical factors in the plaque rupture: (i) fibrous cap thickness; (ii) stenosis ratio; (iii) lipid core width and (iv) lipid core length. The output predicted is the maximum maximal principal stress (MPS) occurred in an atherosclerotic coronary vessel with the input dimensions. For this purpose, an idealized and parametric coronary vessel model has been performed using FEM in order to train the machine learning.

THE ATHEROMA PLAQUE PROBLEM

A 3D parametric model of the coronary artery with atheroma plaque was developed in ABAQUS. Healthy (adventitia and media) and diseased (fibrotic and lipid) tissue was considered in the model. The geometrical parameters used to define and design the idealized coronary plaque anatomy were as follows: lipid length *(l)*, stenosis ratio *(sr)*, fibrous cap thickness *(fc)* and lipid core ratio *(w)* (see Figure 1) [1].

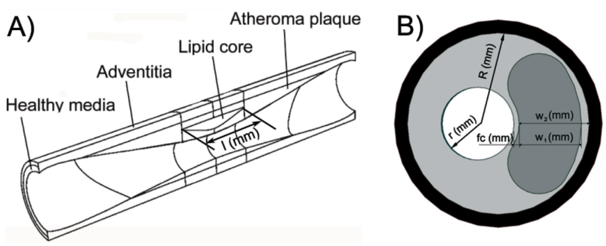

Figure 1. dealized geometry of an atherosclerotic arterial model. Transversal section. (B) Geometrical parameters shown on the cross central section of the atherosclerotic vessel.

The arterial wall and fibrous plaque were modelled as anisotropic and isotropic materials respectively. In vitro experiments have shown that human atherosclerotic materials generally fracture under a threshold stress close to 247 kPa. Therefore, an maximal principal stress threshold of 247 kPa [3] was used in this study for the transition from plaque stability to instability. The FE models were solved under the assumption of finite strains and a systolic pressure of 18.7 kPa (140 mmHg). In order to introduce the longitudinal residual stress, the model was stretched a 4.4 % of the vessel length (longitudinal direction), representing in-vivo conditions [2].

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MATHEMATICAL METHODS FOR REGRESSION

Different machine learning techniques such as Artificial Neural Networks (ANNs) [4] and Support Vector Machines (SVMs) [5] have been used to study the role of stress in plaque vulnerability. The SVMs gives rise to a new class of theoretically elegant learning machines that use a central concept of SVMs - kernels - for a number of learning tasks. Kernel machines provide a modular framework that can be adapted to different tasks and domains by the choice of the kernel function and the base algorithm. MultiLayer Perceptron (MLP), as a representation of the ANNs, is a feed-forward network characterized by its layered structure, each layer consisting of a set of perceptron neurons and its training algorithm.
Furthermore, a linear regression model have been implemented in order to show the presence of high nonlinearities in the problem which reinforces the use of such alternative techniques to solve the regression problem.

RESULTS

In order to compare the results obtained by the three prediction methods, Figure 2 shows the comparison of real points and estimated points by using linear regression, SVM and MLP methods in a set of 50 observations. The SVM and MLP models present very accurate fits between the real and the estimated points with a high correlation between them. The results obtained by SVM are in fact even better than the MLP ones. However, the linear regression model provides a very poor fit between the real and estimated points.

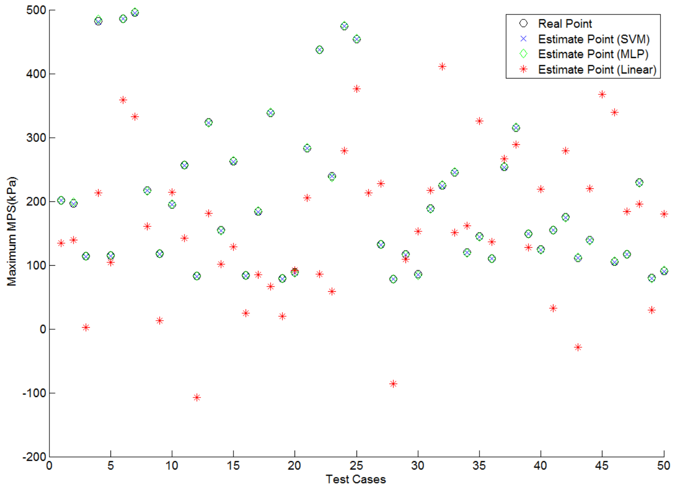

Figure 2. Comparative of real points (o) and estimated points by linear regression (*), SVM (x) and MLP (◇) models in a set of 50 observations.

To play up the importance of computational efficiency, the computational costs of the different methods studied can be compared. For the ANN and SVM, the computation train time is 7 ± 3 and 5 ± 2 minutes, respectively (once the optimal parameters have been chosen and depending on the stopping criterion used), and the validation process time is negligible due to ANN and SVM techniques, which only evaluate a function, provide an immediate estimated response. However, once the FEM model has been constructed, the computational cost of each structural analysis is 10 ± 3 hours.

CONCLUSIONS

According to the results obtained, we come to the following conclusion; the ANN and SVM techniques are able to replace FEM simulations to predict the maximum MPS on an idealized coronary model with a good error tolerance and avoiding the time consuming 3D FE analysis.

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