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Predicting Plaque Progression Using Patient-Specific Fluid-Structure-Interaction Models Based on IVUS and OCT Images with Follow-Up

Xiaoya Guo[1], Dalin Tang [1, 2, *], David Molony[3], Chun Yang[2], Habib Samady[3], Jie Zheng[4], Gary S. Mintz[5], Akiko Maehara[5], Jian Zhu[6], Genshan Ma[6], Mitsuaki Matsumura[5] and Don P. Giddens[3, 7]

Abstract: Atherosclerotic plaque progression is generally considered to be closely associated with morphological and mechanical factors. Plaque morphological information on intravascular ultrasound (IVUS) and optical coherence tomography (OCT) images could complement each other and provide for more accurate plaque morphology. Fluid-structure interaction (FSI) models combining IVUS and OCT were constructed to obtain accurate plaque stress/strain and flow shear stress data for analysis. Accuracy and completeness of imaging and advanced modeling lead to accurate plaque progression predictions.

In vivo IVUS and OCT coronary plaque data at baseline and follow-up were acquired from left circumflex coronary and right coronary artery of one patient with patient's consent obtained. Co-registration and segmentation of baseline and follow-up IVUS and OCT images were performed by experts. Baseline and follow-up 3D FSI models with cyclic bending based on merged IVUS and OCT data were constructed to obtain plaque stress/strain and flow shear stress data for plaque progression prediction. Nine factors (6 morphological factors and 3 mechanical factors) including average cap thickness, lipid area, calcification area, lumen area, plaque area, plaque burden, wall shear stress (WSS), plaque wall stress (PWS) and plaque wall strain (PWSn) were selected for each slice. Plaque area increase (PAI) and plaque burden increase (PBI) were chosen to measure plaque progression and serve as the target variables for prediction. All possible combinations of nine factors were fed to a generalized linear mixed model for PAI and PBI prediction and quantification of their prediction accuracies.

[1] Department of Mathematics, Southeast University, Nanjing, 210096, China.

[2] Mathematical Sciences Department, Worcester Polytechnic Institute, Worcester, MA, 01609 USA.

[3] Department of Medicine, Emory University School of Medicine, Atlanta, GA, 30307, USA.

[4] Mallinckrodt Institute of Radiology, Washington University, St. Louis, MO, 63110, USA.

[5] The Cardiovascular Research Foundation, Columbia University, New York, NY, 10022, USA.

[6] Department of Cardiology, Zhongda Hospital, Southeast University, Nanjing, 210009, China.

[7] The Wallace H. Coulter Department of Biomedical Engineering, Georgia Institute of Technology, Atlanta, GA, 30332, USA.

[*] Corresponding Author: Dalin Tang. Email: dtang@wpi.edu.

In this paper, prediction accuracy was defined as the sum of sensitivity and specificity. The optimized predictor combining 9 factors gave the best prediction for PAI with accuracy=1.7087 (sensitivity: 0.8679; specificity: 0.8408). PWSn was the best single-factor predictor for PAI with accuracy=1.5918 (sensitivity: 0.7143; specificity 0.8776). A combination of average cap thickness, calcification area, plaque area, PWS and PWSn gave the best prediction for PBI with accuracy=1.8698 (sensitivity: 0.8892; specificity: 0.9806). PWSn was also the best single-factor predictor for PBI with accuracy=1.8461 (sensitivity: 0.8784; specificity 0.9677). Although WSS was commonly accepted as an important factor for plaque progression, it showed relatively poor ability for prediction of plaque progression in any measure (accuracy, sensitivity, specificity of PAI: 1.0607, 0.0893, 0.9714; PBI: 1.5431/0.6811/0.9032).

Combining morphological and mechanical risk factors may lead to more accurate progression prediction, compared to the predictions using single factor. PWSn is better than WSS for plaque progression using single factor. IVUS+OCT formed basis for accurate data for morphological and mechanical factors.

Keywords: Vulnerable plaque, OCT, IVUS, plaque progression, patient-specific model, FSI.

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