International Journal of Biosensors & Bioelectronics

Opinion

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# What are the possibilities of machine learning techniques on the mechanical characterization of biological tissues?

Volume 6 Issue 1 - 2020

Martínez J,[1] Pérez-Rey I,[2] Cilla M[3]
[1]Department of Applied Mathematics I, University of Vigo, Spain
[2]Department of Natural Resources and Environmental Engineering, University of Vigo, Spain
[3]Centro Universitario de la Defensa de Zaragoza, Spain

**Correspondence:** Dr. Javier Martínez Torres, Department of Applied Mathematics I, University of Vigo, Escuela de Ingeniería de Telecomunicación, Campus de Vigo 36310, Spain, Tel +34 986 812 247, Email javmartnez@uvigo.es

**Received:** November 12, 2019 | **Published:** January 22, 2020

## Opinion

The experimental study of the mechanical properties of biological tissues is of paramount importance. A good knowledge of the mechanical response of biological materials (like tissues or organs) is needed as a source of information to be introduced into computational models that can serve to correctly reproduce the associated mechanical behavior. Classical engineering testing has been applied to biological materials[1–3] to obtain their properties. Simple tension, planar biaxial and inflation tests are considered the main techniques for the measurement of the mechanical response of blood vessels. The most resorted one, regarding its simplicity and versatility, is the uniaxial test, with particular application to soft biological tissues.[4–7] This technique also presents the feature of being applicable to very small samples. A common practice in the field of mathematical modelling or computational simulation is the use of experimental data to estimate different material model parameters, resorting for that purpose to a strain energy function (SEF), all included in the continuum theory of large deformation hyper-elasticity. The constitutive modelling of soft biological tissues has recently constituted a very active field of research.[8] These materials have commonly been modelled as hyper-elastic continua embedded into continuum mechanical formulations. In this line, one of the main tasks considers the determination of appropriate strain energy density functions, from which local mechanical quantities are obtained. Several constitutive laws have been proposed for soft tissue modelling.[1,9–11], which may be suitable depending on the kind of soft biological tissue at stake. Holzapfel et al.[12,13] proposed the most common SEFs for modelling the behavior of blood vessels accounting for two preferred directions, incorporating fiber dispersion with respect to the deterministic preferred orientation direction, and the work presented by Gasser et al.[14] which includes microstructural information in the model by means of the assumption of a fiber orientation distribution function.

Constant search for effective solutions to the problem of the parameter fitting of soft biological tissues has been put forward by Cilla et al.[15] proposing the use of machine learning techniques (MLTs) among which are: support vector machines (SVMs), bagged or bootstrap-aggregated decision trees (BDTs) and artificial neural networks (ANNs). Machine learning techniques consider algorithms able to learn and make predictions from data. Complex algorithms, which can be trained to reproduce the behavior of a model,[16,17] represent the main feature. MLT's are quite multidisciplinary, with applicability to many different areas, such as electronics,[18] industry,[19] earth sciences,[20,21] space science[22] or language[23] among many others. These techniques have also been applied to different clinical applications like the assessment of electrocardiograms, diagnosis of breast cancer, prediction of femur loads, or optimization of hip implant geometries.[24–28] They have also been used for treating cardiovascular diseases.[29–33] MLT's can be proposed as good candidates to identify different material model parameters, and we strongly believe that the use of these mathematical tools could successfully help to improve the characterization of soft biological tissues. Moreover, the use of MLTs also presents certain advantage in terms of computational costs, reducing computation time in comparison to gradient-base methods, where this time becomes indefinite, searching for an appropriate initial seed. Therefore, MLTs can be likely positioned as good candidates to replace gradient optimization methods that lead to fit the material parameters in the experimental testing of samples of soft biological tissues.[34]

## Funding details

None

## Acknowledgments

None.

## Conflict of interests

Authors declare that there is no conflict of interest.

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**Citation:** Martínez J, Pérez-Rey I, Cilla M. What are the possibilities of machine learning techniques on the mechanical characterization of biological tissues? *Int J Biosen Bioelectron.* 2020;6(1):1–2. DOI: 10.15406/ijbsbe.2020.06.00179