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A framework for modelling the biomechanical behaviour of the human liver during breathing in real time using machine learning

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A B S T R A C T

Progress in biomechanical modelling of human soft tissue is the basis for the development of new clinical applications capable of improving the diagnosis and treatment of some diseases (e.g. cancer), as well as the surgical planning and guidance of some interventions. The finite element method (FEM) is one of the most popular techniques used to predict the deformation of the human soft tissue due to its high accuracy. However, FEM has an associated high computational cost, which makes it difficult its integration in real-time computer-aided surgery systems. An alternative for simulating the mechanical behaviour of human organs in real time comes from the use of machine learning (ML) techniques, which are much faster than FEM. This paper assesses the feasibility of ML methods for modelling the biomechanical behaviour of the human liver during the breathing process, which is crucial for guiding surgeons during interventions where it is critical to track this deformation (e.g. some specific kind of biopsies) or for the accurate application of radiotherapy dose to liver tumours. For this purpose, different ML regression models were investigated, including three tree-based methods (decision trees, random forests and extremely randomised trees) and other two simpler regression techniques (dummy model and linear regression). In order to build and validate the ML models, a labelled data set was constructed from modelling the deformation of eight *ex-vivo* human livers using FEM. The best prediction performance was obtained using extremely randomised trees, with a mean error of 0.07 mm and all the samples with an error under 1 mm. The achieved results lay the foundation for the future development of some real-time software capable of simulating the human liver deformation during the breathing process during clinical interventions.

1. Introduction

The use of computer technology for surgical planning and also for guiding surgical interventions, commonly referred to as computer-aided surgery (CAS), has spread rapidly in the last decades. CAS can be conducted by means of a number of medical imaging technologies, such as X-ray computed tomography (CT), magnetic resonance imaging (MRI), X-ray radiography, and medical ultrasound. Such technological progress in medicine has enabled the introduction of minimally-invasive surgical techniques, which limit the size of incisions needed compared to traditional open surgeries. Thus, the recovery time for the patient, as well as the associated pain and risk of acquiring infections, is reduced. On the other hand, the main drawbacks of these surgical techniques are the limited mobility for the surgeon and the loss of direct contact with the operation site. In particular, CAS systems have allowed to assist surgeons during surgical interventions in real time, minimising the problem of visibility and, therefore, maximising their precision, while reducing invasion into human bodies. Therefore, in the literature, different methods have been applied to assist surgeons

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especially for liver segmentation (Göçeri, 2013, 2016). When performing surgical interventions on internal organs, such as the liver or the breast, the inclusion of biomechanical models that simulate their mechanical response during the intervention is becoming increasingly important in CAS. An accurate biomechanical model of an organ can significantly improve the performance of the surgical technique, as well as predict the outcome of the intervention. Therefore, progress in biomechanical modelling of human organs is the basis for the development of new clinical applications capable of improving the diagnosis and treatment of some diseases (e.g. cancer), as well as the surgical planning and guidance of some interventions. In this sense, a considerable research effort has been made in order to simulate the biomechanical behaviour of the soft tissue (Meier, López, Monserrat, Juan, & Alcañiz, 2005).

Many research works have been focused on using spring–mass methods to simulate the organ deformation in real time due to their simplicity of implementation and their low computational complexity (Delingette, Subsol, Cotin, & Pignon, 1994; Duysak, Zhang, & Ilankovan, 2003; Kenedi, Gibson, Evans, & Barbenel, 1975; Waters, 1992). However, spring–mass models do not allow to reproduce the existing non-linear behaviour of the soft tissue and, therefore, they lead to inaccurate modelling of the mechanical response of the organs.

Instead, the finite element method (FEM) can provide a more physically-realistic and accurate solution by using knowledge about the soft tissue or organ (e.g. organ geometry, elastic constants and boundary conditions of the problem). In fact, FEM is one of the most popular methods used to predict the deformation of the human soft tissue in medical applications (Brock, Dawson, Sharpe, Moseley, & Jaffray, 2006; Brock et al., 2008; Ruiter et al., 2006).

FEM is a well-known numerical method for the simulation of the mechanical behaviour of a continuum body (Zienkiewicz & Taylor, 1989). In FEM, an approximate discrete representation of the organ under study can be obtained by dividing the organ in a high number of elementary building components called finite elements, which are interconnected at points called nodes that define the element size. Finite elements can use physical properties, such as elastic properties, thus integrating tissue characteristics into the organ model. The entire set of these components is called mesh, which is defined through nodes and elements. A mesh is usually built from volumetric images (e.g. CT or MRI) of the organ. The individual equations that govern the mechanical behaviour of the finite elements under external loads are assembled into a larger system of equations that models the entire organ. An approximate solution of these equations can be found through computations on the nodes. Since the number of the equations to solve is proportional to the number of nodes, the larger the number of nodes, the more accurate the solution.

Despite its high accuracy, the use of FEM is limited due to the high computational cost involved. Hence, FEM has been typically used to perform off-line simulations of non-linear/complex behaviours and, therefore, its integration in CAS systems has been difficult due to real-time requirements (i.e. the organ models used in CAS must be deformed in the same way as the real organs, and at the same time). Several techniques have been proposed to reduce the computational time of conventional FEM in clinical applications, such as parallel processing algorithms (Inoue et al., 2006; Székely et al., 2000), the use of graphics processing units (GPU; Courtecuisse et al., 2010) or model reduction techniques (González, Aguado, Cueto, Abisset-Chavanne, & Chinesta, 2016; Niroomandi, Alfaro, Cueto, & Chinesta, 2008; Niroomandi et al., 2013). For example, Székely et al. (2000) used parallel processing algorithms to speed up FEM when simulating the deformation of the uterus due to the interaction with the surgical instruments. Inoue et al. (2006) employed FEM in real time for the development of a liver surgical simulator by means of the use of parallel processing, coupled with volume rendering (i.e. using a relatively coarse volumetric mesh with less than 400 nodes). In other research (Courtecuisse et al., 2010), a GPU implementation was used to significantly improve the computational cost of FEM in the simulation of the interactions between the medical devices and the liver. With regard to the use of model reduction techniques, Niroomandi et al. (2008) applied a new strategy based on proper orthogonal decomposition (POD) techniques to the real-time simulation of the cornea deformation due to the palpation with the surgical tool. Later on, Niroomandi et al. (2013) presented a novel approach based on the use of the so-called proper generalised decomposition (PGD) techniques (i.e. a generalisation of POD techniques), which was also applied to the simulation of the deformation of the liver due to its interaction with the scalpel. Although the commented techniques led to good performance, they were computed only for an organ (i.e. unique geometry and unique elastic constants). Therefore, they could be applied only to predict deformations of that particular organ. This was due to the difficulty in introducing the geometry and the elastic constants as input parameters (i.e. external selectable parameters) into the models based on FEM, since they were fixed parameters required for the construction of the explicit biomechanical model of the organ. Nevertheless, some successful research works have been recently carried out in this regard. For instance, González et al. (2016) presented an approach combining PGD and kernel principal component analysis (kPCA) that was applied to simulate the liver deformation, in which the shape of the liver was also considered to be an external selectable parameter by using several livers with different geometries when building the algorithm, thus making the proposed modelling framework more general. In spite of some promising recent efforts, the development of FEM-based models that can accurately predict the deformation of soft tissue in real time is still a challenge in the field of CAS. In this sense, as computational capacity is increasing rapidly from year to year, it is expected that, in the future, FEM-based simulations will be run in real time and, therefore, they could be used for clinical applications. However, to date, it is not possible to perform real-time simulations based on FEM and, consequently, new techniques that require less computational cost than FEM are arising.

A possible alternative to FEM-based models for simulating the mechanical behaviour of human organs in real time could come from the use of data-driven modelling. In this modelling approach, data are used to feed a supervised machine learning (ML) model in order to find a function of the input variables (e.g. external load applied to the tissue, biomechanical parameters or elastic constants, and the corresponding geometry of the soft tissue) that can approximate the known outputs (e.g. deformation of the soft tissue), with this function being capable of generating an output for future unseen inputs (Izenman, 2008). Hence, the performance of a ML model depends mainly on the collected data and the chosen learning algorithm. Therefore, the ML model does not require an explicit biomechanical model of the organ, as happens in FEM, but it performs simulations based only and exclusively on data. Within this framework, FEM can be used to generate data that the ML model uses to estimate the mapping function (i.e. training samples). Thus, ML models can extract the underlying properties of training samples, for which the deformations are known, and, then, predict soft tissue deformation when exerting a new load. The main advantage of data-driven modelling compared to FEM is that, although the estimation of the mapping function might be very time-consuming, once this training process is done off-line, ML models are able to provide solutions in real time for complex biomechanical behaviours of organs.

Most of the research works using data-driven modelling in this field have been focused on the real-time simulation of haptic interactions with organs (i.e. soft tissue deformation with cutting