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Editorial

Multimodal medical imaging (CT and dynamic MRI) data and computer-graphics multi-physical model for the estimation of patient specific lumbar spine muscle forces

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ABSTRACT

Computer-graphics multi-physical model has been used to assist the clinician in their decision-making processes. In particular, patient specific musculoskeletal modeling using medical imaging data and physical laws has demonstrated great potential for future clinical analysis of the lumbar spine. The main objective of this present work was to propose a data-driven modeling workflow to create computer-graphics multi-physical model from multimodal medical imaging data to extract useful clinical simulation knowledge leading to better diagnosis and treatment of human diseases such as low back pain. Computed Tomography (CT) data and tissue-based physical laws were used to create geometries as well as to compute full patient specific anthropometrical properties of a patient specific multi-physical lumbar spine model. Kinematical range of motion and spinal curvatures were derived from in vivo dynamic MRI. Then, these multimodal data were combined into the developed model to estimate the lumbar spine muscle forces using inverse dynamics and static optimization. Finally, kinematic behavior of the developed model was evaluated. As results, maximal estimated forces of all muscle groups range from 3 to 40 N for hyperlordosis motion. The higher muscle forces were estimated in iliocostalis lumborum pars lumborum muscle group. The simulated spinal curvatures ranging from 2.7909 to 3.1745 (1/m) are within the range of values (from 2.02 to 9.6142 (1/m)) measured from in vivo dynamic MRI. This study suggested that multimodal medical imaging data derived from CT and dynamic MRI could be of great interest in the development of computer-graphics multi-physical model as well as in the estimation of kinematical ranges of motion, their evaluation and muscle forces for biomechanical applications.

1. Introduction

Knowledge extraction from biomedical data is one of the most challenging topics in the health engineering [1–3]. From biomedical informatics point of view, knowledge could be derived from complex multimodal and multidimensional data [4–8]. In the context of biomedical applications, there are many approaches to extract the knowledge such as machine learning or physics-based simulation [9]. Physics-based simulation approach deals with the use of multimodal biomedical data and computer-graphics multi-physical

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model to quantify unobservable information such as muscle forces during motions. Once this information is obtained, it could be used to assist the clinicians in their medical decision-making.

Lumbar spine is one of the most important load-sharing structures of the human body. In addition to its protective function for vital internal organs, this structure allows internal and external loads to be transmitted through back muscles, intervertebral joints, ligaments and discs in a coordinative manner [10]. Lumbar spine muscles play an essential role in the generation of spinal motions. The coordination of these muscles contributes to the stability of the trunk and the whole body under internal and external loadings. In fact, the understanding of this complex mechanical behavior of the lumbar spine structures plays an important role in the diagnosis of low back pain as well as in the prescription of appropriate and optimal functional rehabilitation treatment planning [11–16]. For these purposes, musculoskeletal modeling of the lumbar spine is commonly used to provide information (e.g. tissue stress, muscle force or joint loading) inside the lumbar spine structures and to determine how the mechanical behavior of lumbar spine works in normal and abnormal cases.

Lumbar spine ranges of motion are commonly acquired using medical imaging (e.g. 2D radiography [17] or biplanar radiography [18] or dual fluoroscopic imaging [19] or Upright MRI [20]) or motion capture techniques (e.g. electromagnetic tracking system [21] or computerized dynamic motion analysis devices [22,23] or 3D motion tracking system with implanted bone pins [24]). Medical imaging techniques provide internal accurate lumbar spine ranges of motion while motion capture provides external ranges of motion. However, imaging techniques provide only quasi-static motions rather than real dynamic motion [25]. Moreover, due to limited range of motion and spatial/temporal image resolution, medical imaging approach needs further developments and investigations to provide accurate motion data. Furthermore, invasive character of some techniques limits their use in vivo [17,18,24] even they provide accurate motion data. Consequently, the first objective of this present study was to use non-invasive conventional dynamic MRI technique to provide in vivo spinal kinematic data reflecting the real lumbar spine motions.

In the literature, a number of in silico deformable lumbar spine models have been developed to study the in vivo and in vitro tissue stress under internal and external loading conditions [26–33]. Medical imaging techniques such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) and finite element method allow lumbar spine model to be developed partially in a subject or patient specific manner. Besides, in silico rigid multi-body models of the lumbar spine ranging from basic free body diagram [34] to 3D musculoskeletal model [35–39] have been developed. These 3D lumbar spine rigid multi-body models showed variation of the number of muscles to be considered. For example, LifeMOD/ADAMS model includes 6 erector spinae muscle fascicles [40]. AnyBody model includes 154 muscle fascicles [37]. Enhanced AnyBody model has 214 muscle fascicles [39]. The most physiologically detailed musculoskeletal model is the OpenSIM model including 238 muscle fascicles [38]. Moreover, passive stiffness structures (Intervertebral Disc (IVD)) and intra-abdominal pressure (IAP) activations were also taken into consideration [39]. Some models were used to analyze the postural effect and stabilities or to optimize the correction of spinal deformities [36,41]. Other models were developed to be shared and reused to investigate a range of research questions [37,38]. These models used static optimization to solve the redundancy problem (i.e. number of muscles contributed into a specific motion is greater than the number of physical law equations describing this motion) for the muscle force estimation [42,43]. Hill-based models [44] ranging from simplest to full versions were used to describe the trunk muscle behavior. The simplest version deals with the consideration of only maximal muscle force [36,37,39,45] in the optimization algorithm to estimate muscle forces. There is no Force–Length–Velocity relationship due to the lack of intrinsic back muscle-tendon properties such as muscle moment arm or tendon slack length. Recently, full Hill-based muscle model was integrated into 3D musculoskeletal model for the better description of the simulation muscle behavior [38]. According to our knowledge, most of these models used generic or parameterized geometries and literature-based properties (e.g. muscle and joint properties, body segment inertial parameters (BSIP)). Moreover, one should note that these models have not been used for clinical applications. In the framework of the application of in silico models for personalized medicine purpose, patient specific data should be derived from medical imaging to provide accurate and reliable data for clinical decision-making purpose [43,46]. The second objective of this present study was to develop a patient specific lumbar spine model with individualized full body segment inertial parameters (BSIP) and partial muscle properties derived from CT data.

For these purposes, a data-driven modeling workflow was proposed to create computer-graphics multi-physical model from multimodal medical imaging data to extract useful clinical knowledge leading to better diagnosis and treatment of human diseases such as low back pain. Moreover, literature kinematic range of values was commonly used to perform dynamic simulation [37,38]. The use of literature data should be evaluated before its use for a clinical application. Consequently, in this present study, we used in vivo kinematic data derived from dynamic MRI to evaluate the kinematical behavior of the simulation results of developed model.

2. Materials and methods

2.1. Data-driven modeling workflow for the development of 3D patient specific lumbar spine musculoskeletal model

The workflow consists of following steps (Fig. 1): 1) CT-based patient data acquisition; 2) segmentation of all lumbar spine bony vertebrae; 3) 3D reconstruction of surface-based vertebral models and computing of their individualized body segment inertial parameters (BSIP); 4) intervertebral joint (IVD) modeling; 5) muscle modeling using Hill-based rheological model; 6) multi-body dynamics using motion data and inverse dynamics; 7) muscle force estimation using static optimization; and 8) model analysis.

2.1.1. CT data acquisition

A Computed Tomography (CT) conventional routine protocol was performed to acquire the anatomical lumbar spine images of one patient (female: 60 year old, 65 kg body mass, 160 cm height, 25.39 kg/m^2 Body Mass Index (BMI)) at the National Center for