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Uncertainty Modeling of Input Data for a Biomechanical System of Systems*

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Abstract— **Biomechanical models simulating pathologies need assumptions and often have to deal with data from different sources. We proposed a biomechanical system of systems (BSoS) including two modeling (biomechanics and knowledge-based) approaches to understand the impact of musculoskeletal pathologies leading to propose better diagnosis and appropriate treatment prescription. Moreover, uncertainty of input data was modeled leading to quantify their impact on the simulation results. The architecture of our BSoS including different constituent systems was presented and discussed. Novel knowledge-based fusion p-boxes were developed for uncertainty modeling purpose. Case study was performed on the musculoskeletal simulation. Discussion was addressed.**

I. Introduction

Living systems such as the human musculoskeletal system are complex biological systems. The understanding of the behaviors of related tissues and structures in interaction using biomechanical rigid or deformable models [1]-[3] plays an important role to perform an appropriate diagnosis as well as to prescribe an appropriate treatment for musculoskeletal diseases such as children with cerebral palsy or post-polio. However, most of the models cannot simulate pathologies as simplified assumptions are performed [2]. Recently, we proposed a new modeling approach based on knowledge engineering methods such as ontology [4] and traditional and advanced data mining [5]-[6] to understand the impact of pathologies of the musculoskeletal system on the gait in Biomechanics. This approach provides evidence-based facts and knowledge for the better comprehension of the behaviors of musculoskeletal system under pathological impact. Moreover, our previous confrontation between the physics-based simulation and the knowledge-based modeling approaches [6] showed that these two approaches are closely complementary for better understanding of musculoskeletal disorders leading to best diagnosis and treatment prescriptions. In fact, the integration of these approaches should be of great interest to benefit their complementary advantages and to limit their weakness. However, this integration needs an innovative engineering method. Furthermore, these two approaches use multidimensional and multimodal biomechanical data (e.g. morphological, mechanical, kinematic, kinetic and electromyography (EMG) properties of the musculoskeletal system) as input data for simulation and modeling purposes. These data are highly heterogeneous and subject to the uncertainties due to the human variability, protocols parameters and experimental techniques. Subsequently, these uncertainties need to be modeled and mastered to improve the safely and the reliability of diagnosis and simulation results.

The notion of system of systems has been recently introduced in the engineering system field [7]. From an engineering point of view, a system is defined as a group of functionally, physically and/or behaviorally interactive, independent, material or non-material components. A system of systems (SoS) is a set of useful systems integrated into a larger system to achieve a unique set of tasks [8]. Recently, a healthcare system of systems was introduced to analyze and exploit the human brain as well as the orthopedic kinematic analyses using medical imaging techniques such as 2-D X-ray fluoroscopy, ultrasound or magnetic resonance imaging [9]. In fact, system of system approach could be an appropriate approach to integrate our physics-based simulation and knowledge-based modeling systems. Furthermore, uncertainties of input data need to be modeled and mastered leading to provide their reduction strategy for such a complex system.

Probability boxes (p-boxes) approach was introduced recently with real potential applications [10]. The p-boxes structures deal with non-parametric and parametric p-boxes with known sample distribution. Recently, theoretical aspect of the p-boxes has been improved with new structures such as generalized p-boxes [11] or Bayesian p-boxes with multiple random quantities and dependent parameters [12]. In fact, the p-boxes are flexible structures for the modeling of random and epistemic uncertainties. Thus, the p-boxes could provide basic mathematical structures to develop a generic framework dedicated for our application in the field of Biomechanics. The objectives of this present work were, on the one hand, to develop the architecture of a biomechanical system of systems (BSoS) integrating physics-based and knowledge-based modeling approaches. In the other hand, we developed an uncertainty modeling method for our BSoS. A case study was performed on the modeling of morphological muscle data uncertainties and their impact.

II. Biomechanical System of Systems

A. Architecture

Our biomechanical SoS is defined as an inter-disciplinary and heterogeneity SoS including material and non-material systems in which each system interact with others to achieve a unique set of tasks such as input data acquisition, data

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processing, physics-based simulation, knowledge-based modeling and user interaction. The architecture of our biomechanical system of systems is shown in Figure 1.

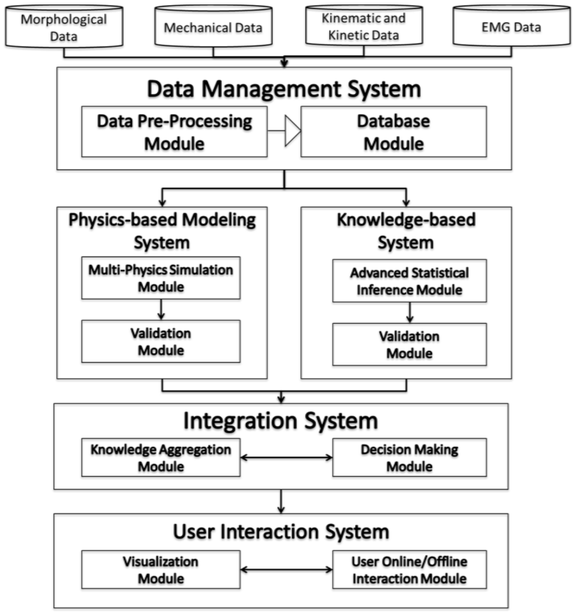

Figure 1. Architecture of our biomechanical system of systems

Our BSoS consists of the following constituents systems:

- Data management system aiming to manage the multi-dimensional (morphological, mechanical, kinematic, kinetic and EMG) and multi-modal (medical imaging techniques, 3D motion capture) data from different data acquisition sources. This system consists of data pre-processing and database modules.

- Physics-based modeling system dealing with the modeling and simulation of the human musculoskeletal system in interaction with external environment using mechanical engineering approaches [2]. This system integrates a multi-physics simulation module and a validation module.

- Knowledge-based system relating to the modeling of musculoskeletal system using knowledge-based engineering approaches such as ontology, advanced data mining, and artificial intelligence methods to perform statistical inference function [5]. This system integrates an advanced statistical inference module and a validation module.

- Integration system aiming to aggregate knowledge from multi-physics simulation and knowledge-based modeling to provide evidence-based facts and knowledge for clinical decision-making. This system consists of a knowledge aggregation module and a decision-making module.

- User interaction system aiming to manage the interaction between the results of our biomechanical SoS and the end users such as clinicians or biomedical researchers or biomedical engineers. This system consists of visualization and user online/offline interaction modules.

B. Input Data Uncertainties Specification

Data uncertainty has two distinct types. The first one is the random uncertainty regarding the variability of a parameter of interest under its systematic (intrinsic) functional and behavior variations. The second one is the epistemic uncertainty dealing with the lack of knowledge, the conflicting evidence, or the ignorance about a parameter of interest and its measuring protocol. Biomechanical input data relates to both random and epistemic uncertainties. Precisely, biomechanical data are subject to random uncertainty regarding the measured range of value (i.e. intrinsic intra-subject variability and inter-subject variability) of a parameter of interest. The intrinsic intra-subject variability concerns the repeatability and the reproducibility errors while the inter-subject variability is due to the data obtained from different protocols or from different population races/origins or from different experimental techniques. Moreover, biomechanical data are subject to the epistemic uncertainty dealing with the accuracy level of the measuring protocol including experimental and numerical processes. In addition, biomechanical data arise from multiple data sources (i.e. research studies) for one parameter of interest. Consequently, the uncertainty modeling method needs to be general enough to include all these requirements.

III. Uncertainty Modeling of Biomechanical Input Data Using Knowledge-Based Fusion P-Boxes

To model the uncertainties of each biomechanical parameter from multiple acquisition sources and with integration of expert judgment on the accuracy of related measuring protocol, we adapted the p-box structures to develop an enhanced version named knowledge-based fusion p-boxes. Note that the p-box is a probability structure representing simultaneously the random uncertainty (i.e. variability), which is represented by the overall slant of the p-box, and the epistemic uncertainty, which is represented by the breadth between the left and right edges of the p-box [10].

A. Knowledge-based p-box

The knowledge-based p-box F_i^K of $X_j \in \mathcal{R}, j \in \{1, \dots, p\}$ (i.e. biomechanical observable random continuous parameter of interest) having the specified distribution $\mathrm{D_i}$ from source $S_i \in \{S_1, S_2, \dots, S_k\}$ is a parametric p-box enveloping of four $\mathrm{D_i}$ distributions $\left(\mathrm{D_i}\left(\mu_i^l, \sqrt{\sigma_i^l}\right), \mathrm{D_i}\left(\mu_i^l, \sqrt{\sigma_i^u}\right), \mathrm{D_i}\left(\mu_i^u, \sqrt{\sigma_i^l}\right), \mathrm{D_i}\left(\mu_i^u, \sqrt{\sigma_i^u}\right)\right)$ where mean $\left[\mu_i^l, \mu_i^u\right]$ and standard deviation $\left[\sigma_i^l, \sigma_i^u\right]$ intervals (l means lower bound and u means upper bound) are computed using the following mathematical formulas:

$$\mu_i^l = |\mu_i - \gamma^\mu \times U_i^r| \quad (1)$$

$$\mu_i^u = |\mu_i + \gamma^\mu \times U_i^r| \quad (2)$$

$$\sigma_i^l = |\sigma_i - \gamma^\sigma \times U_i^e| \quad (3)$$

$$\sigma_i^u = |\sigma_i + \gamma^\sigma \times U_i^e| \quad (4)$$

Where γ^μ and γ^σ are scaling constants computed as follows:

$$\gamma^\mu = \begin{cases} \text{quotient}\left(\dfrac{\mu^u}{10}\right), & \mu^u \geq 10 \\ \text{quotient}\left(\dfrac{\mu^u}{10}\right) + 1, & \text{otherwise.} \end{cases}$$

And

$$\gamma^{\sigma} = \begin{cases} \text{quotient}\left(\frac{\sigma^{u}}{10}\right), & \sigma^{u} \geq 10 \\ \text{quotient}\left(\frac{\sigma^{u}}{10}\right) + 1, & \text{otherwise.} \end{cases}$$

μ_i and σ_i are mean and standard deviation of X_j. $U_i^r \in \{0,\ldots,1\}$ is the random uncertainty coefficient computed as $U_i^r = \frac{w_i}{w}$ where $w_i = x_i^u - x_i^l$ is the width of bounds of X_j from data source S_i. $w = x^u - x^l$ is the width of the fused lower and upper bound set where $x^l = Min\{\mu_i^l - \sigma_i^u\}\forall i$ and $x^u = Max\{\mu_i^u + \sigma_i^u\}\forall i$. $U_i^e \in \{0,\ldots,1\}$ is the epistemic uncertainty coefficient of X_j from source S_i. U_i^e is a function of 5 degree of belief coefficients on the experimental and numerical measuring chain as follows:

$$U_i^e \rightarrow \mathcal{R}^5 \rightarrow f(U_i^e) = N_i^X + E_i^{X_{\text{intra-sub}}} + E_i^{X_{\text{inter-sub}}} + E_i^{X_{\text{device}}} + E_i^{X_{\text{processing}}} \quad (5)$$

Where the expert judgment on the doubt of a value based on the number of subject is defined as $N_i^X \in \{0,0.1,0.2\}$, on the intra-subject (repeatability and reproducibility) variability is denoted as $E_i^{X_{\text{intra-sub}}} \in \{0,0.1,0.2\}$, on the inter-subject variability is defined as $E_i^{X_{\text{inter-sub}}} \in \{0,0.1,0.2\}$, on the measuring device error is defined as $E_i^{X_{\text{device}}} \in \{0,0.1,0.2\}$, and on the numerical processing error is defined as $E_i^{X_{\text{processing}}} \in \{0,0.1,0.2\}$. Each error scale ranges from 0 (inaccurate) to 0.1 (acceptable) and 0.2 (accurate).

Graphical illustration of a knowledge-based p-box of a parameter X_j from one data source is shown in Fig. 2. $\underline{F(x)_i}$ *and* $\overline{F(x)_i}$ are the lower and upper probability non-decreasing functions respectively of F_i^K.

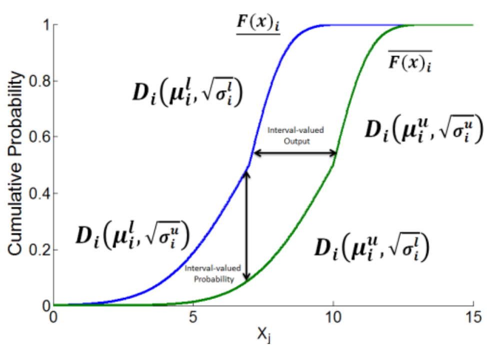

Figure 2. Graphical illustration of a knowledge-based p-box of a parameter X_j with Normal distribution assumption

B. *Knowledge-based fusion p-boxes*

The knowledge-based fusion p-boxes F_F^K of X_j from all k data sources are a combination of different knowledge-based p-boxes of each source S_i. The lower and upper probability bound non-decreasing functions ($\underline{F(x)_F} \leq \overline{F(x)_F}$) of F_F^K is constructed by using the following mathematical formulas:

$$\underline{F(x)_F} = \text{Min}\left\{\underline{F(x)_1}, \underline{F(x)_2}, \ldots, \underline{F(x)_k}\right\} \quad (6)$$

$$\overline{F(x)_F} = \text{Max}\left\{\overline{F(x)_1}, \overline{F(x)_2}, \ldots, \overline{F(x)_k}\right\} \quad (7)$$

Graphical illustration of knowledge-based fusion p-boxes example is shown in Fig. 3.

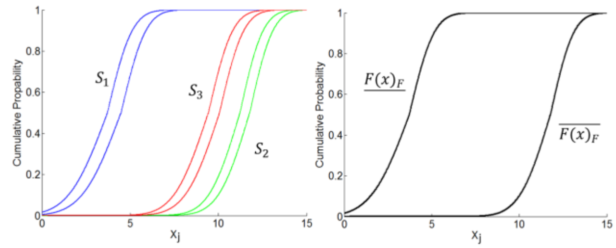

Figure 3. Knowledge-based fusion p-boxed F_F^K of X_j: knowledge-based p-boxes of X_j from 3 separate sources (S_1, S_2, S_3) (left) and fusion p-boxes (right)

IV. CASE STUDY: UNCERTAINTY MODELING OF MUSCLE MORPHOLOGICAL PROPERTIES

Muscle morphological properties are commonly used for musculoskeletal modeling and simulation [3]. However, one-value parameter was usually used as input data. There is no uncertainty consideration for such an input data. In this case study, we modeled the uncertainties of two morphological properties (muscle physiological cross-sectional area ($pCSA_M(cm^2)$) and muscle scaling factor γ_M(N/cm²)) of the rectus femoris muscle. Then their impact on the calculation (Eq. 8) of the peak isometric muscle force F_M^0 was quantified.

$$F_M^0 = pCSA_M \times \gamma_M \quad (8)$$

We collected the values of $pCSA_M$ from 5 sources [13]-[17] and those of γ_M from 3 sources [18]-[20]. These sources arise from reliable scientific search engines such as Science Direct and PubMed. Illustration of range of value of $pCSA_M$ is shown in Fig. 4.

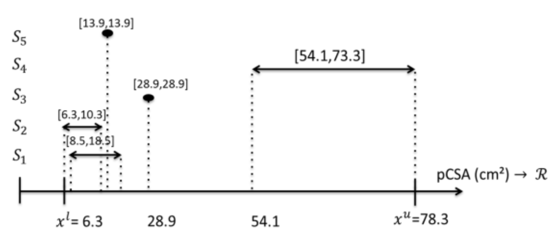

Figure 4. x^l and x^u of the rectus femoris $pCSA_M$ from 5 collected separate data sources $(S_1, S_2, S_3, S_4, S_5)$

Two experimented experts participated into the rating evaluation of the accuracy level of the experimental measuring protocol to compute the U_i^e coefficient. The knowledge-based fusion p-boxes of $pCSA_M$ and γ_M under normal distribution assumption are computed and illustrated in Fig. 5.

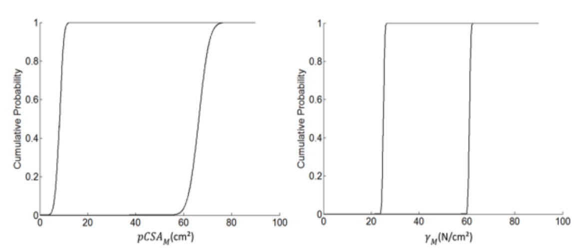

Figure 5. Knowledge-based fusion p-boxes of $pCSA_M$ (left) and γ_M (right)

The impact of the uncertainties of $pCSA_M$ and γ_M on the calculation of the peak isometric muscle force is performed using Monte Carlo simulation with 900 samples. The result is shown in Fig. 6.

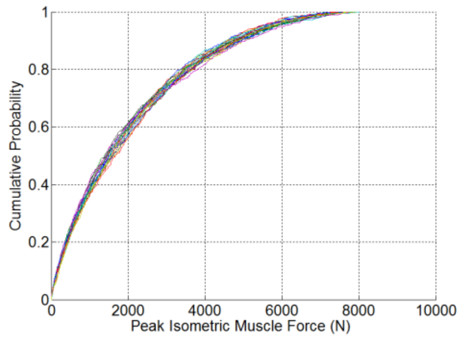

Figure 6. Set of empirical Cumulative Distribution Functions (CDFs) from 10 repeated Monte Carlo runs: peak isometric muscle force F_M^0

V. Discussion

Biomechanical system of systems includes two modeling approaches arising from two separate fields of study (biomechanics and computer science). This integration aims to benefit from the coordination of complex systems to achieve a common healthcare goal with higher significance and relevance. In fact, physics-based simulation system provides basis knowledge on mechanical behaviors of musculoskeletal tissues and structures. Knowledge-based modeling system could aggregate all accumulated knowledge and data to improve the accuracy of the diagnosis, treatment and monitoring processes. Ongoing work on the development of integration system and user interaction system will complete our BSoS. Thus, our BSoS would be of great interest for a better diagnosis and simulation of musculoskeletal disorders leading to propose appropriate treatment prescriptions.

Knowledge-based fusion P-boxes showed their flexibility to model the random and epistemic uncertainties of biomechanics data from multiple sources or from new updated one. Moreover, knowledge-based fusion p-boxes integrate and aggregate the expert's judgments regarding the accuracy level of the experimental measuring protocol into the uncertainty modeling leading to improve also the accuracy of uncertainty representation model. Furthermore, the use of the knowledge-based fusion p-boxes structures coupled with Monte Carlo simulation has demonstrated its potential application for quantifying the impact of input data uncertainties on the output responses.

The results of our case study (i.e. an example of multi-physics simulation of our BSoS) suggest that the output response of a numerical simulation needs to be estimated with a global range of values (Fig. 6). Subsequently, the interpretation of the simulation results with one-value input parameter should be used with caution, especially for a clinical application [21].

To conclude, a biomechanical system of system was introduced. Such a biomechanical SoS has many healthcare applications such as diagnosis and simulation of musculoskeletal disorders or monitoring of functional rehabilitation. Moreover, uncertainty of input data was modeled using novel knowledge-based fusion p-boxes leading to study their impact on the simulation results.

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