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Gait modification and optimization using neural network–genetic algorithm approach: Application to knee rehabilitation

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ABSTRACT

Gait modification strategies play an important role in the overall success of total knee arthroplasty. There are a number of studies based on multi-body dynamic (MBD) analysis that have minimized knee adduction moment to offload knee joint. Reducing the knee adduction moment, without consideration of the actual contact pressure, has its own limitations. Moreover, MBD-based framework that mainly relies on iterative trial-and-error analysis, is fairly time consuming. This study embedded a time-delay neural network (TDNN) in a genetic algorithm (GA) as a cost effective computational framework to minimize contact pressure. Multi-body dynamic and finite element analyses were performed to calculate gait kinematics/kinetics and the resultant contact pressure for a number of experimental gait trials. A TDNN was trained to learn the nonlinear relation between gait parameters (inputs) and contact pressures (output). The trained network was then served as a real-time cost function in a GA-based global optimization to calculate contact pressure associated with each potential gait pattern. Two optimization problems were solved: first, knee flexion angle was bounded within the normal patterns and second, knee flexion angle was allowed to be increased beyond the normal walking. Designed gait patterns were evaluated through multi-body dynamic and finite element analyses.

The TDNN-GA resulted in realistic gait patterns, compared to literature, which could effectively reduce contact pressure at the medial tibiofemoral knee joint. The first optimized gait pattern reduced the knee contact pressure by up to 21% through modifying the adjacent joint kinematics whilst knee flexion was preserved within normal walking. The second optimized gait pattern achieved a more effective pressure reduction (25%) through a slight increase in the knee flexion at the cost of considerable increase in the ankle joint forces. The proposed approach is a cost-effective computational technique that can be used to design a variety of rehabilitation strategies for different joint replacement with multiple objectives.

1. Introduction

Following total knee arthroplasty (TKA), rehabilitation strategies are of significant importance to accelerate patient recovery (Isaac et al., 2005; Klein, Levine, & Hartzband, 2008), reinforce joint functionality (Moffet et al., 2004; Rahmann, Brauer, & Nitz, 2009), decrease gait asymmetry (Zeni, Mcclelland, & Snyder-Mackler, 2011), and augment the durability and life time of knee prostheses (Fransen, 2011; Mont et al., 2006). Gait rehabilitations mainly aim to decrease knee joint loading through minor changes in human gait patterns. However, recognizing the synergistic kinematic changes, required for joint offloading, is a challenging task, hence; computational approaches have been used to facilitate the design procedure. To best of our knowledge, most of the current literature on gait modification strategies have been designed through multi-body dynamic (MBD) analysis (Ackermann & van den Bogert, 2010; Anderson & Pandy, 2001; Barrios, Crossley, & Davis, 2010; Barrios & Davis, 2007; Fregly, D'Lima, & Colwell, 2009; Fregly, Reinbolt, Rooney, Mitchell, & Chmielewski, 2007; Hunt et al., 2008; Mündermann, Asay, Mündermann, & Andriacchi, 2008; Willson, Torry, Decker, Kernozek, & Steadman, 2001). However, iterative "trial-and-error" MBD analysis, that has been performed in such studies, is fairly time demanding which limits the applicability and generality of the method. Hence, a cost-effective computational framework that minimizes the computational cost is of particular interest.

Besides the computational cost, there are a number of aspects that have not been well addressed by the conventional MBD-based framework. *First*, MBD-based approach attempts to reduce the

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peak values of knee adduction moment (KAM) which is not always a reliable measure since decreasing KAM may not necessarily decrease knee joint loading (Walter, D'Lima, Colwell, & Fregly, 2010); and the results of such approach are sensitive to the chosen reference frame (e.g. laboratory, floating reference frames) (Lin, Lai, Chou, & Ho, 2001; Shull et al., 2012). *Second*, joint-offloading gait patterns are likely to decrease the contact area of articulating surfaces that unfavorably may increase the contact pressure at the knee joint (D'Lima et al., 2008). Therefore, reducing the contact pressure should be concerned as the principal goal of rehabilitation design. Conventional computational frameworks however are inherently unable to consider the contact pressure in the design procedure since the conventional methods require an explicit cost function whilst the relation between gait kinematics and the resultant contact pressure has not been stated explicitly before. Also, predicting the contact pressure requires implementing finite element analysis (FEA) which in turn increases the computational cost (Halloran, Ackermann, Erdemir, & van den Bogert, 2010). A cost-effective surrogate which releases the necessity of iterative FEA is therefore of significant advantage. *Third,* previous studies could not reach a general consensus about the contribution of knee flexion to the knee joint offloading. Knee flexion is a key synergetic parameter that is often increased within the clinical execution of the rehabilitation patterns (Barrios et al., 2010; Fregly et al., 2007; Van Den Noort, Schaffers, Snijders, & Harlaar, 2013). Several studies concluded that increasing the knee flexion would reduce KAM (Fregly, 2008; Fregly, D'Lima, & Colwell, 2009; Fregly et al., 2007), whilst others showed that it has no association with KAM (Creaby, Hunt, Hinman, & Bennell, 2013) or may even increase contact pressure at the knee bearing surfaces (D'Lima et al., 2008). A systematic investigation is required to enhance our understanding of the contribution of knee flexion to the knee joint offloading.

Artificial neural networks (ANN) and genetic algorithm (GA) are two relatively new techniques in the field of biomechanics. Artificial neural network (ANN) can be used as a real-time surrogate model with the ability to *learn* a nonlinear relationship. Once a set of inputs and corresponding outputs are presented to the network, it will then "learn" the causal interactions between inputs and outputs. Given a new set of inputs, the trained neural network (surrogate model) can generalize the relationship to produce the associated outputs. The ANN surrogate therefore can be of significant advantage especially when the original model necessitates repeating a time-consuming computation. For example, ANN has been widely used as a surrogate of FEA (Campoli, Weinans, & Zadpoor, 2012; Hambli, 2010; Hambli, 2011; Lu, Pulasani, Derakhshani, & Guess, 2013; Naito & Torii, 2005; Simic, Hinman, Wrigley, Bennell, & Hunt, 2011; Zadpoor, Campoli, & Weinans, 2013). Genetic algorithm is a time-efficient global optimization technique which searches the entire data space to find the best solution (Goldberg, 1989). In each iteration, only potential candidates that better optimize the cost function will survive to the next iteration. Thus, regardless of the initial point, the search data space is iteratively modified and GA will rapidly converge to the global optimum solution. This in turn assures the robustness of the method and minimizes the computational effort required to find the best solution. Moreover, GA is capable of dealing with multi-variable data space, nonlinear input–output interactions and non-explicit, non-differential cost function.

Therefore, the overall aim of this study was to develop a hybrid framework of time delay neural network (TDNN) and genetic algorithm (GA) to address the aforementioned limitations of the literature. In particular this study aimed to (1) optimize the gait pattern in order to minimize the contact pressure at the knee articulating surfaces and (2) investigate the role of knee flexion in knee joint offloading. The advantage of the proposed approach was also compared over the existing knee rehabilitations in the literature.

2. Materials and methods

The proposed computational approach was implemented in the following steps:

Step (1) Experimental gait analysis data were obtained from the literature (Section 2.1), and imported into MBD analysis to calculate gait kinematics and kinetics (Section 2.2). Knee flexion angle and three dimensional knee joint loadings were predicted by MBD, and then served as boundary condition and loading profiles for the finite element simulation to calculate contact pressure (Section 2.3). Gait trials were then outlined via a number of kinematic features and the corresponding maximum contact pressure values (CPRESS-max) (Section 2.4).

Step (2) A time-delay neural network (TDNN) was trained to learn the nonlinear relationship between kinematic features as inputs and the corresponding CPRESS-max values as output (Section2.5).

Step (3) A genetic algorithm (GA) was implemented to search for the optimum kinematic features (optimization variables) which minimized the CPRESS-max at the knee joint bearing surfaces. In this GA, the trained TDNN was served as a real-time cost function to calculate the objective value (CPRESS-max) (Section 2.6).

2.1. Experimental gait data

Experimental gait analysis data of a single subject with unilateral TKA (female, height 167 cm, mass 78.4 kg) was obtained from the literature (https://simtk.org/home/kneeloads; accessed on June 2013). The subject walked with a variety of different gait patterns including *normal*, *medial thrust*, *trunk sway*, *walking pole*, *bouncy*, *crouch*, *smooth* and *fore foot strike*. *Medial thrust*, *trunk sway* and *walking pole* were knee rehabilitation strategies, designed to decrease KAM, whilst the remaining gait trials were different walking patterns to cover the span of executable gait for the subject. Compared to *normal* walking, the subject walked with a slightly decreased pelvis obliquity, slightly increased pelvis axial rotation and leg flexion to implement *medial thrust* pattern. For *trunk sway* pattern, the subject walked with an increased lateral leaning of the trunk in the frontal plane over the standing leg. In *walking pole*, the subject used bilateral poles as walking aids. For each gait pattern, five gait trials were repeated under the same walking condition at a self-selected pace. A total of two complete gait cycles were picked up from each trial, leading to a total of 84 data sets. For further details, see Fregly et al. (2012). Gait trials were recorded in terms of marker trajectory data (Motion Analysis Corp., Santa Rosa, CA) and ground reaction forces (AMTI Corp., Watertown, MA).

2.2. Multi-body dynamic

Experimental ground reaction forces and marker trajectories were imported into the three-dimensional multi-body dynamic simulation software, AnyBody Modeling System (version 5.2, AnyBody Technology, Aalborg, Denmark). A lower extremity musculoskeletal model was used in AnyBody software based on the University of Twente Lower Extremity Model (TLEM) (Klein Horsman, 2007). This model, available in the AnyBody published repository, had 160 muscle units as well as foot, thigh, patella, shank, trunk and thorax segments. Hip joint was modeled as a spherical joint with three degrees of freedom (DOF): flexion–extension, abduction–adduction and internal-external rotation. Knee joint was modeled as a hinge joint with only one DOF for flexion–extension and universal joint was considered for ankle-subtalar complex. Since the assumptions of the simplified knee joint and rigid