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Proposition, identification, and experimental evaluation of an inverse dynamic neuromusculoskeletal model for the human finger

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ABSTRACT

Purpose: The purpose of this study is to develop an inverse dynamic model of the human middle finger in order to identify the muscle activation, muscle force, and neural activation of the muscles involved during motion. Its originality comes from the coupling of biomechanical and physiological models and the proposition of a dedicated optimization procedure and cost function for identifying the model unknowns.

Methods: Three sub-models work in interaction: the first is the biomechanical model, primarily consisting of the dynamic equations of the middle finger system; the second is the muscle model, which helps to identify the muscle force from muscle activation and dynamic deformation for six involved muscles. The third model allows one to link muscle activation to neural intent from the Central Nervous System (CNS). This modeling procedure leads to a complex analytical nonlinear system identified using multi-step energy minimization procedure and a specific cost function.

Results: Numerical simulations with different articulation velocities are presented and discussed. Then, experimental evaluation of the proposed model is performed following a protocol combining electromyography and motion capture during a hand opening–closing paradigm. After comparison, several results from the simulation and experiments were found to be in accordance. The difficulty in evaluating such complex dynamic models is also demonstrated.

Conclusions: Despite the model simplifications, the obtained preliminary results are promising. Indeed, the proposed model, once correctly validated in future works, should be a relevant tool to simulate and predict deficiencies of the middle finger system for rehabilitation purposes.

1. Introduction

Physics-based models have proved their efficiency in modeling human motion and its interaction with the environment [1,2]. They have been usefully used in biomechanics, allowing clinical human motion analysis. Similar models are dominant in robotics and computer graphics [3], since they allow plausible animation and simulation of human-like motion. Furthermore, the importance of such dynamic physical models increases in the field of humanoid robotics, which has matured with faster, more accurate, and more mechanically complex robots. Henceforth, research has begun to expand beyond the usual robotics framework towards an examination of life sciences, for the purpose of better imitating natural motion [3]. The computational modeling approach gives us a systematic way to understand the working principles of the motion genesis. It is important to note that the major interest for generative modeling comes from the interactive relationship between modeling and understanding.

Many recent studies present the biomechanical model of the human hand, particularly in motion, with anisotonic and anisometric muscle contractions [4–6]. In fact, some of these recent works propose 3D inverse dynamic models of the human finger, such as the one developed by Sancho-Bru et al. [4] for estimating the muscle forces responsible for free index finger motions. In another recent study, the same mathematical dynamic model is used but for hand motion modeling [3,5–7]. This system is studied in a static condition by considering only the linear mechanical equations. Vigouroux [8] also worked on biomechanical modeling of the human hand; the objective of his model was to deduce the muscle forces from movement using a non-linear equations system. Buchanan et al. [9] proposed a neuromusculoskeletal dynamic modeling for the upper limb. The objective of his forward model was to estimate the muscle forces from neural activations (extracted from surface EMG signals)

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Nomenclature

$\vec{\alpha} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{pmatrix}$ α_1, α_2 and α_3 are the flexion angles of DIP joint, PIP joint; and MCP joint respectively (Fig. 2)

$\dot{\vec{\alpha}} = \begin{pmatrix} \dot{\alpha}_1 \\ \dot{\alpha}_2 \\ \dot{\alpha}_3 \end{pmatrix}$ represents the angular velocities

$\ddot{\vec{\alpha}} = \begin{pmatrix} \ddot{\alpha}_1 \\ \ddot{\alpha}_2 \\ \ddot{\alpha}_3 \end{pmatrix}$ represents the angular accelerations

$\overline{M}_{ext} = \begin{pmatrix} M_{ext1} \\ M_{ext2} \\ M_{ext3} \end{pmatrix}$ M_{ext1}, M_{ext2} and M_{ext3} are the external moment applied on the system constituted by the phalanx P_4; P_4 and P_3; and P_4, P_3 and P_2 respectively (Fig. 2).

a_i	muscle activation of muscle i.
u_i	neural activation of muscle i
ε_i	muscle deformation of muscle i.
$\dot{\varepsilon}_i$	muscle deformation velocity of muscle i.
F_i	muscle force of muscle i.
e(t)	post-processed EMG.
DIP	distal interphalangeal joint.
PIP	proximal interphalangeal joint.
MCP	metacarpophalangeal joint.
FDS	flexor digitorum superficialis muscle.
FDP	flexor digitorum profundus muscle.
EDC	extensor digitorum communis muscle.
LU	lumbricalis muscle.
RI	dorsal interossei muscle located on the radial side of the finger.
UI	dorsal interossei muscle.
β_i	force distribution coefficient of muscle i or muscular bound i.
m_i	weight of phalanx p_i

in order to pilot a virtual arm. Shao et al. [10] presented a musculoskeletal model to estimate muscle forces using the joint's kinematic and sEMG data. Paclet et al. [11] focused their research efforts on the study of the biomechanics of the upper limb tendon transfers; however, this work is limited to the deduction of muscle forces as force generators [12].

Identifying forces, activations and deformations in the hand muscles and joints when fingers move is an important theme in biomechanics due to the fact that finger motions representing 54% of all human motor capacities [6]. Estimating these variables has applications in many fields such as medicine, ergonomics, prevention, rehabilitation [13,14] and sports performance evaluation [15]. This functional knowledge can help to prevent the appearance of pathologies by improving the ergonomics of work tools and preventing the risk of injury associated with movements or sports techniques.

However, most of the proposed models focus on mechanistic concepts which do not consider the neural activation patterns and motion intents of the Central Nervous System (CNS). With the need to develop an artificial organ to replace the finger or a surgical rehabilitation in the case of partial impairment, the conception of an inverse dynamic model of the finger neuromusculoskeletal system becomes necessary to understanding the functional behavior of such complex physiological systems.

The main objective of this paper is to propose a dynamic inverse model linking middle finger kinematics to the estimation of muscle forces, muscle activations, and neural activations of six muscles: the three extrinsic muscles (EDP,EDC, and FDS) and three intrinsic muscles (LU, RI, and UI) involved in middle finger motion. For this purpose, a specific nonlinear multistep optimization procedure is applied using a specific energy minimization cost function. After, for illustration purposes, some simulations are launched and an attempt to experimentally evaluate these simulations is realized. Practically, the estimated neural activation curves, estimated using sEMG recording techniques, are compared to those estimated from the proposed model and tuned using motion capture data. Finally, the obtained results and both model and experimental protocol limitations are discussed.

2. Methods

The proposed model consists of three sub-models as shown in Fig. 1. It extents a previous model that estimates muscle forces, muscle activations, and neural activations for the middle finger by dividing motion into quasi-static positions [16] to the isokinetic motion case. The first sub-model is the finger biomechanical model. It takes the finger anatomy and its kinematic data as input to estimate, by inverse optimization procedure, the muscle forces that are involved. The second sub-model is the biomechanical muscle model. This model simulates the muscle-tendon complex and links the provided muscle force to the muscle deformation (length modification), the muscle activation (correlated to the number of active Motor Units (MUs) in the muscle), and the muscle velocity contraction. Finally, the third sub-model, namely the neural/muscle activation, allows for the modeling of the relation linking neural intent, estimated from the sEMG data, to the muscle activation. It represents the neural part of the proposed neuromusculoskeletal model. The neural activation, defined by Buchanan et al. [9], describes the intermediate stage, representing a simplified neural intent decoding process from the recorded sEMG signal to muscle activation. In fact, the neural activation is the intent of muscle contraction tuned by the CNS. It can differ from the muscle activation which corresponds to the amount of recruited MUs normalized by the number of all available MUs. This difference is represented by a non-linear relationship function. The sEMG neural activation is the intent of muscle contraction estimated from the sEMG signal, after rectification and filtering, since a non-invasive and direct access to the real neural activation is unrealizable. Ideally, the two curves should be superimposed.

The proposed computational architecture permits one to deduce the neural intent from finger dynamic data as shown in Fig. 1. Evaluation of the proposed model is completed by comparing neural activations, estimated by the model fed by estimated finger kinematic data from motion capture, to neural activations deduced from sEMG recordings from the three extrinsic muscles (EDC, EDP, and FDS) involved in the finger motion, following a specific experimental opening-closing hand protocol.

The proposed study will be presented as follows. In Section 2.1, we present and detail the finger dynamic biomechanical model. Then, the mechanical muscle-tendon model is described in Section 2.2. After, in Section 2.3, we present the estimation procedure for calculating the model unknowns, and some simulated data obtained using the proposed model. Section 2.4 describes a preliminary experimental protocol for evaluating simulation results.