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Chapter XII

Estimation of Muscle Forces About the Ankle During Gait in Healthy and Neurologically Impaired Subjects

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ABSTRACT

This chapter describes a biomechanical model of the forces about the ankle joint applicable to both unimpaired and neurologically impaired subjects. EMGs and joint kinematics are used as inputs and muscle forces are the outputs. A hybrid modeling approach that uses both forward and inverse dynamics is employed and physiological parameters for the model are tuned for each subject using optimization procedures. The forward dynamics part of the model takes muscle activation and uses Hill-type models of muscle contraction dynamics to estimate muscle forces and the corresponding joint moments. Inverse dynamics is used to calibrate the forward dynamics model predictions of joint moments. In this chapter we will describe how to implement an EMG-driven hybrid forward and inverse dynamics model of the ankle that can be used in healthy and neurologically impaired people.

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INTRODUCTION

It is difficult to estimate muscle forces during human movements. Such forces cannot be measured directly apart from implantation of force sensors into the muscles — a painful procedure that is difficult to use on multiple muscles and would likely cause unnatural changes in the way such muscles are activated (e.g., limping). Although biomechanical models are commonly used to analyze human motion, estimation of individual muscle forces remains problematic as it is a difficult modeling task to do with reasonable accuracy. The main reason for this difficulty is that the musculoskeletal system is redundant: there are an infinite number of combinations of muscle forces that could create a desired limb movement or, in most cases, even a single joint moment.

Nevertheless, there are two approaches that have been used with reasonable success. The first uses a mathematical approach, calculating muscle forces based on optimization of muscle forces according to a user-defined cost function (e.g., Neptune, 1999; Anderson & Pandy, 2001). The other approach uses information about how the nervous system activates the muscles, as recorded from electromyograms (EMGs) and from this the muscle forces are estimated (e.g., Lloyd & Besier, 2002; Buchanan et al., 2004). The later approach will be the focus of this chapter.

Accurate estimation of muscle forces is important to study the neural control of movement, design of advanced prosthetics and to provide clinical tools for rehabilitation. In this chapter the focus will be on applications pertaining to the control of the human ankle and will conclude with an application to gait in a subject who has had a stroke.

MODEL FLOW

There are two fundamentally different approaches employed to study human movement and kinetics: forward and inverse dynamics. Each has strengths and weaknesses and we shall use a hybrid method that takes advantage of the strengths of each method (Figure 1).

Inverse dynamics relies on information about position and ground reaction forces. By simple application of fundamental rigid-body dynamics (e.g., Newton's Laws), joint moments can be calculated from the kinematic and external force data. From joint moment and musculoskeletal geometry one might try to calculate muscle forces. However, the body is a redundant system and multiple muscles contribute to each joint moment. Therefore, the force distribution among the muscles that span a joint cannot be readily determined. In our application, inverse dynamics will only be used to determine joint moments.

Forward dynamics depends on neural command, which can be estimated from electromyograms. EMG is measured directly from each of the interested muscles. *Muscle activation dynamics* is the process by which the EMG (measured in millivolts) is converted to muscle activation, a(t), a dimensionless time varying signal between zero and one (Figure 1). In combination with joint position and velocity data, muscle activation is used to estimate muscle force by means of a process called *muscle contraction dynamics*. The total joint moment due to the muscle forces is easily computed from forces and corresponding muscle-tendon moment arms. In a typical forward dynamic analysis,

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