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Identifying transient patterns of *in vivo* muscle behaviors during isometric contraction by local polynomial regression

Xin Chen[a], Huiying Wen[a], Qiaoliang Li[a], Tianfu Wang[a], Siping Chen[a], Yong-Ping Zheng[b], Zhiguo Zhang[c,*]

[a] *School of Medicine, Shenzhen University, National-Regional Key Technology Engineering Laboratory for Medical Ultrasound, Guangdong Key Laboratory for Biomedical Measurements and Ultrasound Imaging, Shenzhen, China*
[b] *Interdisciplinary Division of Biomedical Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong, China*
[c] *School of Chemical and Biomedical Engineering and School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore, Singapore*

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ABSTRACT

Polynomial regression is the most common method to estimate the relationship between muscle signals and torque during muscle contraction, but it is not capable of characterizing important transient patterns in the signal–torque relationship that only exist during short bursts of torque but may convey detailed information of muscle behavior. In this study, we proposed an integrated data analysis approach based on local polynomial regression (LPR) to identify transient patterns in the signal–torque relationship. For each subject, the LPR method can represent electromyography (EMG), mechanomyography (MMG) and ultrasonography (US) features as nonlinear functions of torque and can further estimate the derivatives of these signal–torque nonlinear functions. Further, a number of break points can be detected from the derivatives of the signal–torque relationships at the group level, and they can segment the signal–torque relationships into several stages, where multimodal features change with torque in different dynamic manners. Eight subjects performed isometric ramp contraction of knee up to 90% of the maximal voluntary contraction (MVC). EMG, MMG and US were simultaneously recorded from the rectus femoris muscle. Results showed that, for each feature, the whole torque range were clearly segmented into several distinct stages by the proposed method and the feature–torque relationship could be approximately described by a piecewise linear function with different slopes at different stages. A critical break-point of 20% MVC was detected during the isometric contraction for all muscle signals. As compared with the conventional regression methods, the proposed LPR-based data analysis approach can effectively identify stage-dependent transient patterns in the feature–torque relationships, providing deeper insights into the motor unit activation strategy.

1. Introduction

In vivo muscle behaviors during contraction deliver important physiological information about structure and function of muscles. Various recording techniques have been developed to measure *in vivo* muscle behaviors from different aspects and the most commonly-used techniques include electromyography (EMG) [1], mechanomyography (MMG) [2], and ultrasonography (US) [3]. EMG is composed of electrical contributions made by active motor units (MUs) during muscle contraction and MMG is the recording of low-frequency lateral oscillations of active MUs. On the other hand, the architecture of skeletal muscle is a primary determinant of muscle function, and the morphological change of muscle can be obtained by US.

These muscle signals (EMG, MMG, and US) are in nature time-course data, but it is often of greater advantage to represent these signals as functions of the torque for understanding how muscle behaviors change with the torque output. The signal–torque relationship can be estimated by polynomial regression [4], artificial neural networks [5], and support vector machine [6]. The most widely used polynomial regression has shown that EMG, MMG, and US exhibit different response patterns with respect to torque. The amplitude of EMG/MMG is usually characterized by linear or curvilinear increase with the level of torque in isometric ramp and step contractions [7,8]. Morphological parameters (such as muscle thickness, fiber pennation angle, fascicle length, cross-sectional area [CSA], etc.) measured by US exhibit substantially different changing patterns with the increase of torque [9].

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* Corresponding author. Tel.: +65 67904485; fax: +65 67947553.
E-mail address: zgzhang@ntu.edu.sg (Z. Zhang).

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Polynomial regression estimates the global signal–torque relationships by specifying a certain functional form for data of the whole recording period, but it is not flexible enough to describe transient relationships between signal and torque. As a consequence, important transient patterns that only exist during short bursts of torque but may convey detailed information of muscle behavior (such as at which level of torque the muscle behavior changes abruptly and in which degree the change is) cannot be identified by polynomial regression. Although it is speculated that torque-related muscle behavior consisted of piecewise smooth functions [10], no quantitative investigation has been developed yet. Therefore, a new approach for quantitatively and objectively identifying transient patterns of *in vivo* muscle behaviors is desirable.

In this study, we proposed a new and integrated data analysis approach based on local polynomial regression (LPR) [11–13] to identify torque-related transient patterns of EMG, MMG and US features. This new approach is based on a more realistic and general assumption that the underlying signal–torque relationship is a smooth function (up to the second order), of which the 1st and 2nd derivatives convey important information regarding the transients in the nonlinear relationship. For example, positive 1st derivatives imply that features change with the torque in the same direction, and negative values in 2nd derivatives imply that the co-variation between features and torque gets smaller (a summary of the information contained in derivatives is provided in Section 2). However, it is non-trivial to estimate the derivatives of feature–torque functions from non-uniformly spaced feature points along the torque, because a straightforward differentiation of the regression functions estimated from noisy data samples will cause an accumulation of errors increasing with the derivative order [14].

To estimate regression functions and their derivatives from noisy and non-uniformly sampled data for each subject, a popular non-parametric regression method, LPR, is used. Compared with the conventional polynomial regression, the LPR method is data-driven and the regression functions are determined locally from windowed data. In this study, at any given level of torque, the LPR method fits polynomials to a fraction of EMG/MMG/US samples within a window centered at the torque to estimate the regression functions. Importantly, LPR is also an effective technique to estimate derivative functions from 1st and 2nd difference quotients of noisy data samples, as proved in [14]. Therefore, LPR is adopted in the study to estimate the nonlinear feature–torque functions and their derivatives for EMG/MMG/US features.

Further, based on evidence in previous studies such as [10,15], we approximated the group-level feature–torque relationships as piecewise linear functions (with different slopes in different torque ranges) from subject-level LPR derivative estimates. The break-points of the piecewise functions were detected from LPR derivative estimates of all subjects with statistical testing, and the whole torque range was accordingly segmented into several distinct stages. The changing direction and changing speed of each feature were estimated at each stage and statistically compared between stages to show how features vary with torque in different patterns. In summary, the results on experimental data provide strong evidence supporting the stage-dependent patterns of *in vivo* muscle behaviors during isometric contraction.

2. Methodology

2.1. Signal acquisition

Multimodal measurements were taken in eight (five males, three females) healthy volunteers (mean ± SEM, age = 31.4 ± 5.7 years; body weight = 59.2 ± 9.8 kg; height = 166.4 ± 8.3 cm). The study was approved by the local ethics committee. The subject was seated with the right leg at a flexion angle of 90° on a test bench of an isokinetic dynamometer (Humac Norm Testing and Rehabilitation System, Computer Sports Medicine, Inc., Massachusetts, USA). The subject was required to put forth his maximal effort of isometric knee extension for a period of 6 s. The maximal voluntary contraction (MVC) was defined as the highest value of torque recorded during the entire isometric contraction. In each test trial the subject was instructed to perform ramp contractions to produce torques increasing linearly from zero up to 90% MVC in 6 s. During each contraction, a template torque, serving as a target, and the output of the subject's torque, were displayed simultaneously on a computer screen, which helped the subject to adjust his torque production to track the target torque in real-time. Three trials were repeated with a rest of 5 min between adjacent trials. The ultrasound images of the rectus femoris (RF) muscle were obtained by an ultrasonic scanner (EUB-8500, Hitachi Medical Corporation, Tokyo, Japan). The ultrasound probe was fixed by a custom-designed multi-degree adjustable bracket. The long axis of the probe was arranged perpendicularly to the long axis of the thigh on its superior aspect, 40% distally from the knee (measured from the anterior superior iliac spine to the superior patellar border). The ultrasound image was digitized by a video capture card (NI PCI-1411, National Instruments Corporation, Austin, TX, USA) with a frame rate of 25 Hz and resolution of 0.15 mm; the instant when every frame was captured was recorded as timestamp for off-line signal processing.

Two surface bipolar Ag–AgCl EMG electrodes (Axon System, Inc., NY, USA) were placed on the RF muscle belly parallel with the long axis of the muscle on both sides of ultrasound probe, and a reference EMG electrode was placed near the kneecap. The MMG signal was detected using an accelerometer (EGAS-FS-10-/V05, Measurement Specialties, Inc., France) fixed with two-sided tape. The EMG and MMG signals were amplified by a custom-designed amplifier with a gain of 2000, filtered separately by 10–400 Hz, 5–100 Hz bandpass analog filters, and digitized by a 12-bit data acquisition card (NI-DAQ 6024E, National Instruments Corporation, Austin, TX, USA) with a sampling rate of 1 kHz. The isometric torque output from the dynamometer was also sampled by the NI-DAQ card in synchronization with the ultrasound image capture. Ultrasound images, EMG, MMG, and torque signals were simultaneously collected and stored by custom-developed software.

2.2. Integrated data analysis approach

A new integrated data analysis approach, including feature extraction, local polynomial regression, and derivative-based piecewise function estimation, to identify transient patterns of *in vivo* muscle contraction. First, we extracted a set of time-varying features from EMG and MMG signals as well as US images. Second, for each feature and each subject, LPR is used to estimate the smooth function of the signal–torque relationship and its 1st and 2nd derivatives. Third, a group-level statistical test (a pointwise one-sample *t*-test against zero at each torque value) on LPR-based derivative estimates can reveal a piecewise linear function for each signal–torque relationship. These three steps will be detailed in the following.

2.3. Feature extraction

The EMG and MMG signals were segmented into 256-ms epochs. The length of epochs can affect the signal-to-noise ratio of estimation and the tracking ability to follow the change of EMG and MMG. The epoch length of 256 ms is empirically selected and this length has shown good performance in our previous study [9]. The center of each EMG/MMG epoch was aligned in time with the corresponding ultrasound image according to the timestamp, so that