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A Multimodal Investigation of in vivo Muscle Behavior: System Design and Data Analysis

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Abstract—The study is aimed to investigate in vivo behaviors of the rectus femoris muscle during isometric contraction by integrating simultaneously recorded electromyography (EMG), mechanomyography (MMG), and ultrasonography (US). We developed an experimental platform for simultaneous acquisition of EMG, MMG, US, as well as the torque, during isometric muscle contraction. Features from multimodal signals and images were then automatically extracted and calibrated to present time-varying characteristics of muscle behaviors. We further applied local polynomial regression (LPR) to reveal nonlinear and transient relationships between multimodal muscle features and torque. The results suggested that the proposed multimodal signal acquisition and integration are capable of providing novel and complete information about in vivo muscle contraction. The proposed experimental platform is a potentially useful tool for muscle assessment in various clinical and practical applications.

Keywords—electromyography, mechanomyography, medical instrument, multimodal integration, ultrasonography

I. INTRODUCTION

In vivo muscle behavior during contraction delivers important information about structure and function of muscles, and is a central topic in neuromuscular research. Various recording techniques have been developed to measure in vivo muscle behavior and the most common techniques include electromyography (EMG) [1], mechanomyography (MMG) [2], and ultrasonography (US) [3].

EMG is composed of electrical contributions made by the active motor units (MUs) during muscle contraction and MMG is the recording of the low-frequency lateral oscillations of active MUs and is considered to be the mechanical counterpart of the MU electrical activity. The time and frequency characteristics of EMG and MMG, such as the amplitude and spectrum, are considered to reflect the motor control strategies [1] and [2]. The architecture of skeletal muscle, defined as the geometric arrangement of muscle fibers, is a primary determinant of muscle function. Therefore, the morphological change of muscle is an alternative measurement of muscle activities [4]. Since US offers unique frequency characteristics of EMG and MMG, such as the root mean square, RMS) to represent continuous muscle activities, whereas few techniques have been developed to automatically extract dimensional parameters (e.g. CSA) from continuously-recorded US images (e.g. 30 frame/sec). Second, there is a lack of a standard method to synchronize three modalities. Because US has significantly different sampling rate than EMG and MMG and all three modalities of signals are non-uniformly distributed as functions of torque, it is desirable to calibrate the torque coordinates of the three modalities prior to the comparison. Third, most of previous studies utilized polynomial regression to estimate the EMG/MMG/SMG-to-torque relationships during the whole contraction. However, polynomial regression is not flexible enough to describe nonlinear and transient relationships between torque and EMG/MMG/US because it is based on a specific functional form (linear or quadratic) for all observed data. Muscle’s nonlinear and transient response patterns are important single measurement or imaging technique. Therefore, in order to obtain a more complete description of the neuromuscular mechanisms of muscle contraction, it is necessary to attain simultaneously measured multimodal signals of muscles. Since EMG, MMG, and US provide electrical, mechanical, and morphological measurements of muscles, respectively, their simultaneous recordings are expected to enhance the understanding the muscle contraction mechanisms.

Simultaneous measurement of MMG and EMG has been used to examine the electrical and mechanical aspects of muscle function during some specific actions [7], providing novel and meaningful information regarding muscle contraction. On the other hand, some studies have investigated the muscle contraction using simultaneously recorded US and EMG [6]. It is considered that US can measure the morphological change of muscle during contraction and is complementary to EMG. Furthermore, US would be particularly valuable for deep muscles that are inaccessible by surface EMG [6]. However, most of the multimodal investigations of in vivo muscle behaviors are still in a very preliminary state. Little work has been done to simultaneously record and integrate three modalities: EMG, MMG, and US.

Investigation of simultaneously recorded multimodal signals is important because it could provide insight into the relationships among different aspects and contributes to a better understanding of the fundamental mechanism of muscle contraction. But it faces several difficulties in the analyses of data and images. First, EMG and MMG signals can easily produce instantaneous parameters (i.e. root mean square, RMS) to represent continuous muscle activities, whereas few techniques have been developed to automatically extract dimensional parameters (e.g. CSA) from continuously-recorded US images (e.g. 30 frame/sec). Second, there is a lack of a standard method to synchronize three modalities. Because US has significantly different sampling rate than EMG and MMG and all three modalities of signals are non-uniformly distributed as functions of torque, it is desirable to calibrate the torque coordinates of the three modalities prior to the comparison. Third, most of previous studies utilized polynomial regression to estimate the EMG/MMG/SMG-to-torque relationships during the whole contraction. However, polynomial regression is not flexible enough to describe nonlinear and transient relationships between torque and EMG/MMG/US because it is based on a specific functional form (linear or quadratic) for all observed data. Muscle’s nonlinear and transient response patterns are important.

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because they may convey detailed information of muscle behavior (such as at which level of torque the muscle behavior changes and in which degree the change is).

This study is aimed at developing a systematic experimental and data analysis platform for simultaneous acquisition and multimodal integration of EMG, MMG, and US. The diagram of the developed platform is shown in Fig. 1. The system has three essential parts, which are detailed as follows.

1. Signal acquisition: Based on our work in [6], a frame-synchronized system for simultaneous acquisition of EMG, MMG, and US is introduced. This system enables continuous collection and storage of ultrasound images, surface EMG, MMG and torque signals for subsequent analysis.

2. Feature extraction: We use a novel image processing method, named constrained mutual information-based free-form deformation (C-MI-FFD) tracking, to automatically extract morphological parameters from US images [6]. The C-MI-FFD method makes US a practical technique to characterize continuous morphological changes of muscles.

3. Regression analysis: We explore the nonlinear and non-stationary relationship between multimodal features and torque. A local polynomial regression (LPR) [8] is introduced to present the continuously identified features of three modalities as smooth functions of a uniform grid of torque values, making it possible to compare the EMG/MMG/SMG-to-torque relationships. More importantly, LPR is capable of identifying dynamic and transient response patterns of muscles with the increase of torque.

II. METHODOLOGY

A. Signal Acquisition

Multimodal measurements were taken in eight healthy volunteers (five males, three females). 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 seconds. 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 band-pass 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.

B. Feature Extraction

The EMG and MMG signals were segmented as 256-ms epochs. The center of each epoch was aligned in time with the corresponding ultrasound image according to the timestamp, so that the epochs were synchronized with the image sequence in time domain. The root mean square (RMS) values of EMG and MMG were calculated for each epoch and expressed as a percentage of their maximal values at 90% MVC.

Muscle dimensions were measured offline by in-house image processing program. An object tracking method, named C-MI-FFD tracking, was developed to automatically extract dynamic muscle boundary from the ultrasound image sequence. In the C-MI-FFD method, we aim to determine the transformation function which describes the deformation between two successive images by minimizing an MI-based objective function. More details of the C-MI-FFD method can
be referred to [6]. For each trial, the first image in the sequence was selected as reference and the boundary of the RF muscle was outlined with smooth lines by the investigator using ImageJ software (ImageJ, NIH, USA). Then the C-MI-FFD method was applied to track the CSA boundaries in subsequent images. After getting the boundary, muscle thickness was measured as the greatest vertical distance between the anterior and posterior borders from the extracted boundary, and muscle width was measured at 50% of the vertical distance between the anterior and posterior borders in the boundary, perpendicular to the vertical measure.

C. Local Polynomial Regression

Local polynomial regression (LPR) [8] is a flexible and efficient nonparametric regression method in statistics, and it is particularly effective for interpolation and smoothing of non-uniformly sampled data. Compared with polynomial regression that fits a certain functional form to all observed data, the LPR method is more data-driven and the regression functions are determined locally by windowed data. More precisely, at any given point of the independent variable, the LPR method fits polynomials to a fraction of data (dependent variable) within a window centered at the point and having variable window bandwidth. Given the local bandwidth, the polynomial coefficients can be estimated using the weighted least-squares estimator. As shown in [8], the estimation bias of LPR increases while the variance decreases as the window bandwidth increases and there exists an optimal bandwidth at each evaluated point. In our problems, since US/EMG/MMG signals or features may vary considerably over torque, it is crucial to choose a proper local bandwidth to achieve the best basis-variance tradeoff. We adopted an intersection of confidence intervals (ICI) technique [9] to adaptively select variable optimal bandwidth for the best bias-variable tradeoff of the LPR estimator. As a consequence, the LPR method can better capture the dynamic relationship and local information than the conventional polynomial regression. The algorithms of LPR and ICI are omitted to save space, and more details can be found in [8] and [9].

In this study, at each torque sample (uniformly distributed from 0 to 80% MVC with a step of 1% MVC, resulting in 81 torque samples), the LPR used a one-order polynomial to fit one set of multimodal features (multimodal features, RMS_{EMG}, RMS_{MMG}, CSA, thickness, width of US) and the local bandwidth was adaptively selected by the ICI method. With the LPR and the ICI methods, the smooth functions of multimodal features and their first-order derivatives with respect to torque can be estimated.

III. RESULTS

Fig. 2 shows the torque, EMG, and MMG signals of one representative trial. The RMS_{EMG} and RMS_{MMG} curves are also overlapped in the figure. Four US images of the same trial (including the first image, the first image with manually drawn boundary, the image at 50% MVC, and the image at 50% MVC with automatically tracked boundary, width and thickness) are shown in Fig. 3. The corresponding time courses of CSA, width and thickness, which were well extracted using the C-MI-FFD method, are shown in Fig. 4.

Fig. 5 shows the results of LPR, which presented multimodal features as smooth functions of torque. It can be seen that all the multimodal features show considerable nonlinearities. The smooth functions before and after 20% MVC show considerably different patterns in almost all multimodal features, which was not reported in previous studies using conventional polynomial regression method. The turning point around 20% MVC roughly divided the relationship curves into two force regions, and the changing rates of each feature were different in the two regions. This phenomenon was more obvious in US features than in EMG or MMG feature, and it may be caused by the spatial arrangement of the quadriceps femoris muscle group. The RF muscle under test is surrounded by three other muscles, vastus intermedius, vastus lateralis, and vastus medialis, which also contribute to the knee extension. In low force region, the dimensional change of each muscle is relatively small and the effect of space constraint is not obvious since there are initial gaps between the muscles. While in high force region, the space constraint becomes more obvious and this may cause distortion of the RF muscle. Therefore, the US feature changes are affected not only by muscle contraction but also by the space limitation, especially in the high force region. In contrast, the effect of space constraint on EMG/MMG parameters is small and the change trend of the parameter curve is relatively consistent in the whole force range.

IV. CONCLUSION

In this study, we proposed a multimodal method to investigate the contractile behavior of RF muscle in vivo. A systematic experimental and data analysis platform was developed for simultaneous acquisition and multimodal integration of EMG, MMG and US. The LPR analyses presented the features of three modalities as smooth functions of the torque and demonstrated the nonlinear relationship between multimodal features and torque. The results suggested that the proposed multimodal method can provide novel and more complete information of muscle contraction. Thus, it is potentially a useful tool for the muscle assessment in clinical and practical applications.

REFERENCES

Fig. 2. The time courses of (a) EMG, (b) MMG, and (c) torque during a representative trial. The torque signal was overlaid onto the ramp template as it appeared for the subject during the trial. The $\text{RMS}_{\text{EMG}}$ and $\text{RMS}_{\text{MMG}}$ curves are also overlapped in the raw EMG/MMG curve.

Fig. 3. Ultrasound images of the RF muscle in one trial. (a) The first image in the image sequence, where the neighboring quadriceps muscles [vastus lateralis (VL), vastus intermedius (VI), and vastus medialis (VM)] are indicated. (b) The first image in the image sequence, with manually outlined boundary as reference for further image processing. (c) The image at 50% MVC, with automatically outlined boundary, width, and thickness by the C-MI-FFD method.

Fig. 4. Dimensional changes of CSA, thickness and width in a typical trial (the trial shown in Fig. 3).

Fig. 5. LPR of five parameters as functions of torque. Thick black lines are mean values of functions (mean and first order derivative), and thick dashed lines denote mean±SEM.