Nov. 2020
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Muscle Characterization Using System Identification

System Model and System Identification

In many branches of science and engineering, a dynamic system model is referred to as a mathematical equation that describes the behavior of the dynamic system. Nearly every dynamic system we can think of can be described by a mathematical model. Some examples include the tuning of radio antennas, the exchange of oxygen and carbon dioxide occurring between capillary blood vessels and alveoli in a lung, a machine vision system used in autonomous vehicles, the structure of Golden Gate bridge, and control systems in nuclear plants.

System identification is the process of identifying a mathematical model that represents the dynamic behavior of a given system. Accurate knowledge of the mathematical model of a system is crucial in the analysis of a system as it gives the ability to digitally simulate the system behavior. Without spending an inordinate amount of effort and time in building physical systems, we can learn from the simulation how different parameters in the design of the system affect the behavior of the system, and test critical situations.

For this reason, the theory of system identification has been developed alongside control theory [1], and widely used in the field as an important toolbox of algorithms and methods. Additionally, the parameters determined by system identification, along with an appropriate understanding of the fundamental physics, can be interpreted or used to calibrate the physical properties of a system. This has extended the application of system identification to improve advanced sensor technology in many fields such as biomechanics [2,3,4], optics [5,6] and electrochemistry [7,8].

System Identification Techniques

During the process of system identification, a known (or observed) input is applied to the system in question, while the output signal is measured. Then, different mathematical techniques are used to extract the information about the system buried inside the output signal. For example, when the system identification is conducted on the suspension system of a car to analyze its mechanical properties, an oscillating force with a known frequency and amplitude can be given to the system as an input, and the response (e.g. displacement or acceleration) is measured as an output. By collecting experimental data at different frequencies and plotting the magnitude ratio and phase difference between output and input we can construct a so-called frequency response of the suspension system, which is one type of dynamic model. This mathematical model can now be used to predict the behavior of the suspension system, such as how much vertical movement the car will experience as it runs over a speed bump.

The mathematical techniques best suited for a system depend on whether the system behaves linearly or nonlinearly, and whether an a priori model used in the system identification process is parametric (a model represented by the fixed number of parameters) or nonparametric (a model represented by continuous data, such as impulse response). Broad knowledge has been developed within each category of the techniques since the 1970s [9]. The rapid progress of machine learning algorithms is further expanding the scope and applications of system identification.

Muscle System Identification

The mechanical properties of muscles is an important indicator in muscle pathology as well as physical training. Studies have shown that the change of muscle stiffness is strongly related to physical injuries [10], and other muscle properties can also be used to assess some diseases such as Parkinson's [11] and Hoffman's syndrome [12]. Also, aside from the scientific evidence, most people have learned from their own experiences that aching sensations and pain can be caused by swollen, tense, or bumpy parts of their muscles (i.e. knots). For example, after intense running one can readily feel the difference in the stiffness of calf muscles by massaging them.

The common methods of measuring muscle properties include electromyography (EMG) [13], mechanomyography (MMG) [14, 15] and ultrasound using piezoelectric transducers [16]. These methods have been widely used in many biomechanical studies to broaden our understanding of muscle mechanics and its importance to our body. However, such methods typically require complicated data acquisition devices or can only produce meaningful results under research conditions where a number of parameters are tightly controlled. As a result we have rarely heard of “muscle-property-meter” in our daily life as opposed to a thermometer.

Impact Biosystems provides a solution that can bring muscle measurement to our everyday routine using system identification. Unlike most of other measurement techniques which only measures passive signal coming from the muscle (e.g. EMG and ultrasound), our device mechanically perturbs the muscle over time using a probe with carefully designed force input such that the measured output response (i.e. displacement and acceleration) contains meaningful information about the mechanical properties of the muscle. Although the analysis involves algorithms that rely on complicated mathematics, the actuator and sensor in the device are simple enough to be cost effective.

Experimental Results

Our preliminary experiments show that the device can tell clear differences in mechanical properties of bicep muscles after it experiences intense bicep curl exercises (see Figure 1-3). In this experiment, the measured response from the device was analyzed with nonparametric (Figure 1) and parametric (Figure 2 and 3) linear system identification to detect the change in the system model of bicep muscle represented by nonparametric step response (NP-STP) and system parameters (A1, A2, B1, B2, C1, and C2), respectively.

The change in the shape of NP-STP and the value of the parameters indicate that mechanical properties of the bicep changed due to exercises. In fact, all participating subjects also clearly felt such a change in their muscle as they experienced pain and biceps were swollen. However, the significance of the system identification result is that the change can now be quantitatively expressed. This information can provide useful feedback to the device user as it allows them to objectively self diagnose their muscle during the exercise (see Figure 3). Our team is expanding the measurement technique and knowledge on mechanical properties of the muscle using various other mathematical techniques for systems identification (e.g. nonlinear and parametric system identification) with the help of machine learning to improve the accuracy and quality of the analysis.

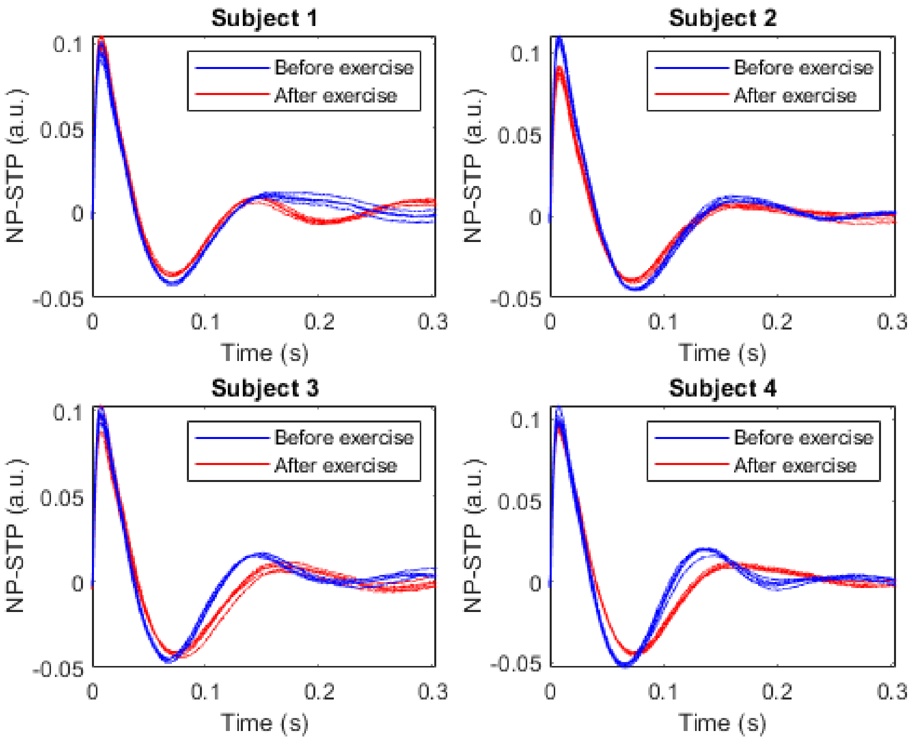

Figure 1. Estimated step responses (n=5) of the bicep of 4 subjects measured before (blue) and after (red) intense bicep curls using nonparametric linear system identification.

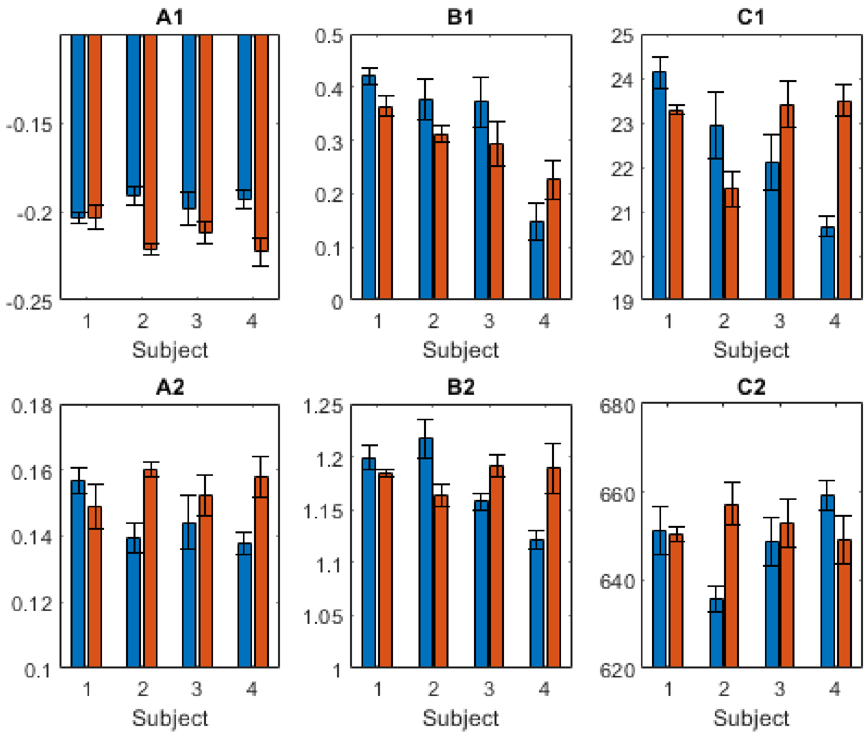

Figure 2. *Estimated parameters (n=5) of the bicep of 4 subjects measured before (blue) and after (red) intense bicep curls using parametric linear system identification.*

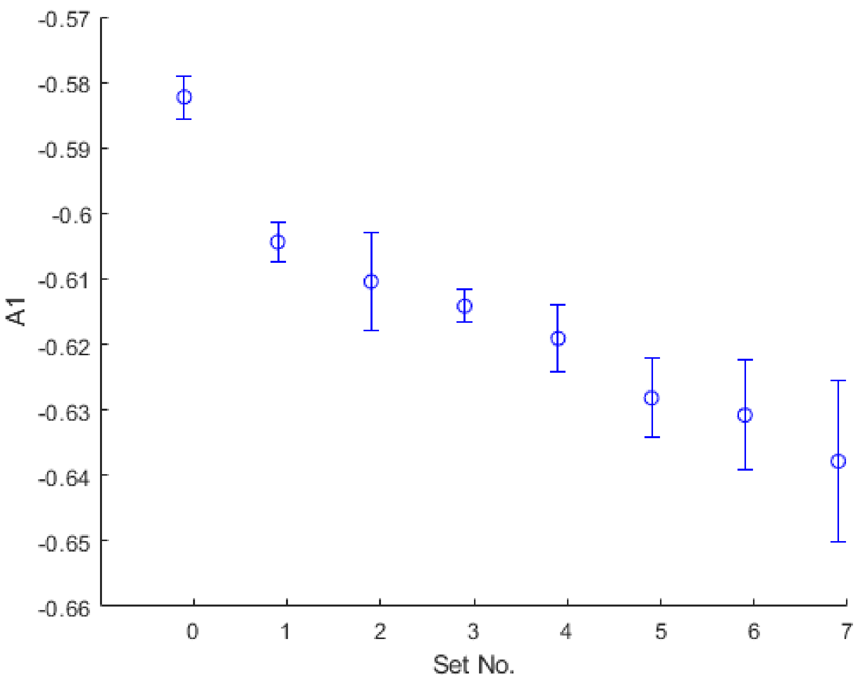

Figure 3. *Estimated parameters (n=5) of the bicep of one subject measured after each set of bicep curls using parametric linear system identification.*

[1] Kumar, P. R., & Varaiya, P. (2015). *Stochastic systems: Estimation, identification, and adaptive control*. Society for Industrial and Applied Mathematics.

[2] HUNTER, I. (1985, January). FROG-MUSCLE FIBER DYNAMIC STIFFNESS DETERMINED USING NONLINEAR-SYSTEM IDENTIFICATION TECHNIQUES. In *Biophysical Journal* (Vol. 47, No. 2, pp. A287-A287). 9650 ROCKVILLE PIKE, BETHESDA, MD 20814-3998: BIOPHYSICAL SOCIETY.

[3] Kearney, R. E., & Hunter, I. W. (1990). System identification of human joint dynamics. *Critical reviews in biomedical engineering*, *18*(1), 55-87.

[4] Chen, Y., & Hunter, I. W. (2013). Nonlinear stochastic system identification of skin using Volterra kernels. *Annals of biomedical engineering*, *41*(4), 847-862.

[5] Inman, S. W. (2011). *Integration of real time oxygen measurements with a 3D perfused tissue culture system* (Doctoral dissertation, Massachusetts Institute of Technology).

[6] Berezin, M. Y., & Achilefu, S. (2010). Fluorescence lifetime measurements and biological imaging. *Chemical reviews*, *110*(5), 2641-2684.

[7] Hází, J., Elton, D. M., Czerwinski, W. A., Schiewe, J., Vicente-Beckett, V. A., & Bond, A. M. (1997). Microcomputer-based instrumentation for multi-frequency Fourier transform alternating current (admittance and impedance) voltammetry. *Journal of Electroanalytical Chemistry*, *437*(1-2), 1-15.

[8] Yoo, J. S., & Park, S. M. (2000). An electrochemical impedance measurement technique employing Fourier transform. *Analytical chemistry*, *72*(9), 2035-2041.

[9] Billings, S. A. (2013). *Nonlinear system identification: NARMAX methods in the time, frequency, and spatio-temporal domains*. John Wiley & Sons.

[10] Howell, J. N., Chleboun, G., & Conatser, R. (1993). Muscle stiffness, strength loss, swelling and soreness following exercise‐induced injury in humans. *The Journal of physiology*, *464*(1), 183-196.

[11] J. Marusiak, K. Kisiel-Sajewicz, A. Jask´olska, and A. Jask´olski, "Higher muscle passive stiffness in parkinson's disease patients than in controls measured by myotonometry," Archives of physical medicine and rehabilitation, vol. 91, no. 5, pp. 800–802, 2010.

[12] I. Klein, M. Parker, R. Shebert, D. Ayyar, and G. S. Levey, "Hypothyroidism presenting as muscle stiffness and pseudohypertrophy: Hoffmann's syndrome," The American journal of medicine, vol. 70, no. 4, pp. 891–894, 1981.

[13] J. P. Halbertsma, A. I. van Bolhuis, and L. N. G¨oeken, "Sport stretching: effect on passive muscle stiffness of short hamstrings," Archives of physical medicine and rehabilitation, vol. 77, no. 7, pp. 688–692, 1996.

[14] M. T. Tarata, "Mechanomyography versus electromyography, in monitoring
the muscular fatigue," Biomed Eng Online, vol. 2, no. 3, 2003. [15] N. Alves and T. Chau, "Automatic detection of muscle activity from mechanomyogram signals: a comparison of amplitude and wavelet based methods," Physiological measurement, vol. 31, no. 4, p. 461,
2010.

[15] M. A. Islam, K. Sundaraj, R. B. Ahmad, and N. U. Ahamed, "Mechanomyogram for muscle function assessment: a review," PloSone, vol. 8, no. 3, p. e58902, 2013.

[16] E. Drakonaki, G. Allen, and D. Wilson, "Ultrasound elastography for musculoskeletal applications," Ultrasound, vol. 85, no. 1019, 2014.