Hybrid Machine Learning and Physics-Based Estimation of Human Joint Mechanics for Remote Monitoring

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Background & Significance

Astronaut health and well-being is imperative for successful human space travel and is a primary concern of NASA's Human Research Program (HRP). Prolonged exposure to low-gravity environments results in muscle atrophy and reduced bone density. Loaded treadmill walking is often prescribed to mitigate these effects, but the major muscles involved in this activity still undergo substantial performance decline. To optimize exercise prescription, one must monitor tissue loading. However, monitoring biomechanics for this purpose is non-trivial, especially since standard techniques employed on Earth are not directly applicable. Practically deployable techniques should be cost efficient, easy to use, and unconstrained. Wearable sensors present a hardware solution, but current signal processing algorithms are either not generally applicable, require many sensors and/or utilize reference vectors unavailable in space flight (e.g. Earth's gravitational/magnetic fields). Thus, new tools are needed to monitor joint mechanics both during space flight and after returning to Earth.

Project Goals

The goal of this project was to combine machine learning and physics-based techniques for analyzing human motion in a hybrid approach. This technique would utilize machine learning regression algorithms where the physics are least-well understood or not sufficiently informed. Similar techniques have proven successful in other fields such as climate science and vehicle tracking, but not for monitoring human biomechanics. Specifically, this project focused on the development of hybrid techniques for estimating knee and ankle joint loading during walking. The developed technique would be validated against standard laboratory methodologies.

Summary of Key Findings

A systematic review of wearable sensor-based regression techniques for human motion analysis found surface electromyography sensors were most often used in this area and that the incorporation of domain specific knowledge often improved performance. In several reviewed papers, the muscle synergy hypothesis was referenced to explain how machine learning algorithms may learn neuromusculoskeletal system dynamics using only a few sensors. The muscle synergy hypothesis explains how muscles work together in a coordinated fashion to control human movement. This finding motivated a potential hybrid solution wherein measured muscle excitations from a subset of muscles could be used to inform the muscle activity of all involved muscles. These signals drive muscle contraction dynamics, the simulation of which informs the joint mechanics used to monitor tissue loading. As a first step towards investigating this potential solution, I developed a Gaussian process-model of muscle synergies during walking which allowed the estimation of unmeasured muscle activity using measurements from a subset of muscles

(Figure 1). A comprehensive investigation of different model structures as well as validation on multiple participants showed the technique estimates muscle activity with high accuracy and comparable to other synergy models. Preliminary analyses suggest the proposed approach can estimate muscle activity for unseen walking speeds (i.e. not used for model training). Work is currently being done to validate this approach for estimating individual muscle force and joint moment using the proposed hybrid technique. Also related to this project, an algorithm was developed to identify foot contact and foot off events during walking using a single sensor. Identification of these events are necessary in the proposed technique to utilize gait phase-specific simplifying assumptions (e.g. null distal contact force during the swing phase). Work from this project has appeared in two peer-reviewed publications (a third is currently under review) and three conference proceedings.

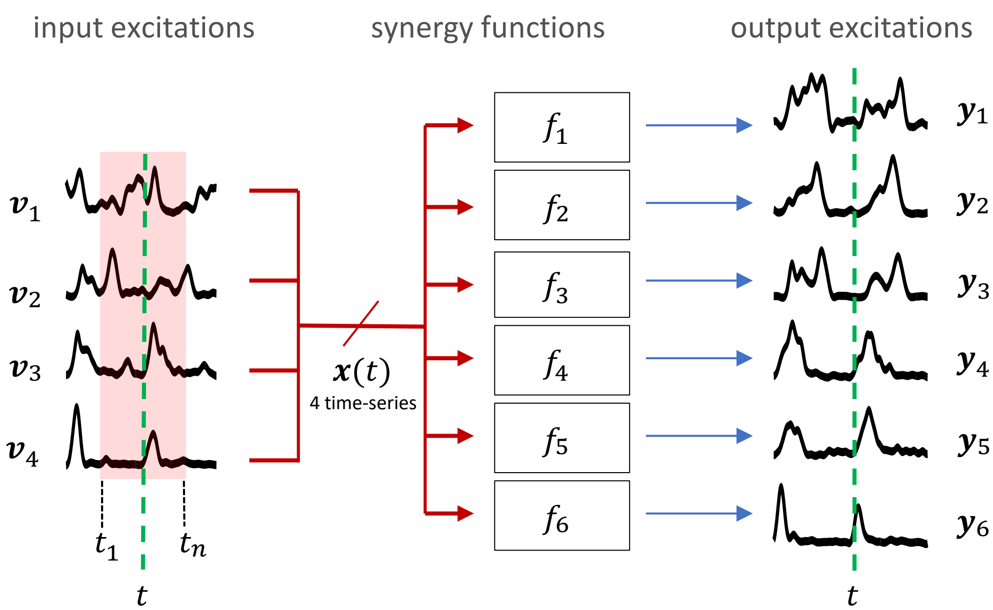

Fig. 1. Visual overview of the proposed estimation of unmeasured muscle excitations using a measured subset. In this example, four muscle excitation time-series are available from measured data (input muscles: $\boldsymbol{v}_1$-$\boldsymbol{v}_4$) and are used to estimate the excitations of six other muscles (output muscles: $\boldsymbol{y}_1$-$\boldsymbol{y}_6$). To estimate the muscle excitation at time t (green dashed line) for a given output muscle, a finite time interval $[t_1 \ t_n]$ (black dashed lines), called the input window (shaded red area), of each input muscle is input to the corresponding synergy function (f_1-f_6). The proposed approach approximates the behavior of the synergy functions using Gaussian process regression.