

EMG INFORMED MUSCULOSKELETAL MODELLING AND DEEP LEARNING TO ESTIMATE MUSCLE MOMENT

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Introduction: Understanding the internal joint biomechanics of the lower limbs during ambulation is potentially useful for augmenting human motion. Several deep learning (DL) approaches have been implemented to estimate biological joint moments [1]-[2] to generalize exoskeleton control across tasks. For instance, our previous study showed that using a temporal convolutional network (TCN), can effectively estimate biological joint moment during different ambulation modes [1]. These algorithms, however, fail to incorporate the underlying biomechanics occurring in the joint, such as muscle tendon unit (MTU) length, muscle force, or individual muscle moments, which may be beneficial for providing optimal assistance during rapid concentric muscle contractions [3]. This study uses a DL TCN with ground truth labels calculated using the Calibrated Electromyography (EMG) Informed Neuromusculoskeletal Modelling Toolbox (CEINMS) [4] and OpenSim [5] to estimate the internal muscle dynamics and joint moments surrounding the knee across a wide variety of ambulatory tasks and movements using common exoskeleton sensors, such as encoders, inertial measurement units (IMUs), and insoles (Fig 1A), calculated from the data in a virtual OpenSim environment [6]. Due to the accuracy of this approach shown in [1], we hypothesized that the TCN would be able to accurately estimate the flexion and extension components of the net joint moment, as well as individual muscle moments for the flexor and extensor muscles spanning the knee joint during human movement.

Methods: Twelve subjects were outfitted with motion capture markers and EMG sensors and were instructed to perform twenty-eight different cyclic and non-cyclic tasks, such as walking, running, jumping, squatting, and turning. Inverse dynamics, kinematics, and muscle analysis were calculated for each subject in OpenSim and EMG data were low pass filtered, rectified, and normalized by maximum contractions recorded across all tasks. The CEINMS Toolbox, normalized EMG activations, and OpenSim muscle moment arms were used to calculate ground truth internal muscle dynamics, such as muscle force, for the muscles spanning the knee which were identified by the OpenSim Gait 2354 model. Individual and combined flexion and extension muscle moments were calculated by multiplying muscle moment arm and muscle force (Fig. 1B) prior to estimation. To estimate muscle moments using the TCN, joint angles, virtual IMU outputs, and virtual insoles simulating ground reaction forces were modelled in OpenSim. These inputs, combined with the individual, flexion, and extension moments spanning the knee joint were fed into the TCN, where a two headed model estimated flexion and extension moment and a seven headed model estimated each individual muscle moment (Fig. 1C).

Results & Discussion: The R^2 of the TCN varied greatly across all muscles when compared to net flexion, net extension, and net biological joint moment (Fig. 1C). The TCN performed most accurately when estimating net biological joint moment with an R^2 of 0.897 ± 0.028 , with a flexion moment R^2 of 0.250 ± 0.031 , and an extension moment R^2 of 0.478 ± 0.036 , with lower accuracy for the individual muscles. Overall, the DL TCN performed better when estimating knee extension rather than flexion, however this could be attributed to having more tasks in our dataset that emphasized extension vs. flexion (i.e., more non-cyclic tasks). In general, R^2 values tended higher in cases where the torque generated by a muscle or muscle group was higher, R^2 tracking was low when a muscle's torque contribution was low.

Significance: The purpose of this study was to determine the resolution of estimating an internal muscle characteristic such as muscle moment during several structured and unstructured tasks with a DL model. While previous studies have shown the efficacy of estimating net biological joint moment [1], little work has been

done to estimate or calculate internal muscle dynamics without the use of invasive or intrusive sensor suites such as ultrasound or EMG. By targeting and estimating different internal muscle moments and states, exoskeleton assistance can potentially be fine-tuned to fill gaps between the user and the device, providing more beneficial assistance during ambulation. Likewise, the ability to separately estimate muscle dynamics such as flexion and extension moment can allow researchers to monitor joint health during different types of activities to better understand and prevent joint injury and degradation.

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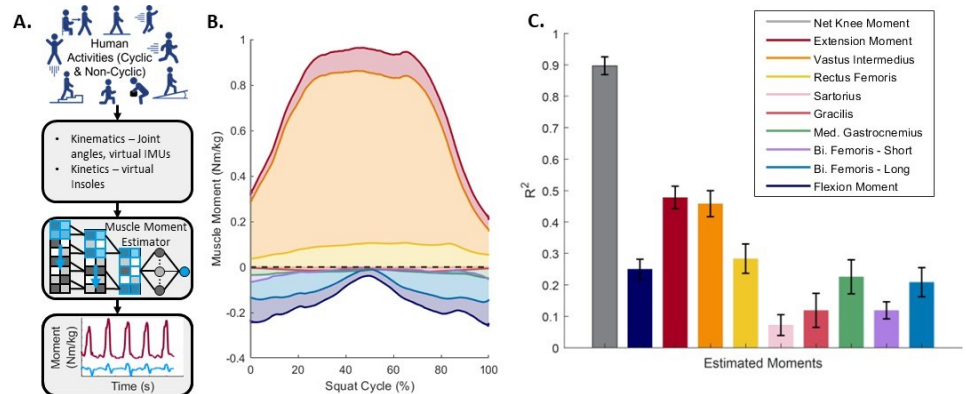


Figure 1: A. Flow chart showing path of data from human activity to muscle moment estimation. B. Contributions of individual muscle forces to net flexion and net extension in the knee for squatting. C. R^2 results from TCN estimation of net knee moment, flexion and extension moment, and individual muscle moment for all cyclic and non-cyclic tasks.