Learning from the Measurable: Predicting Changes in Hill-Type Muscle Parameters from Lateral Pinch

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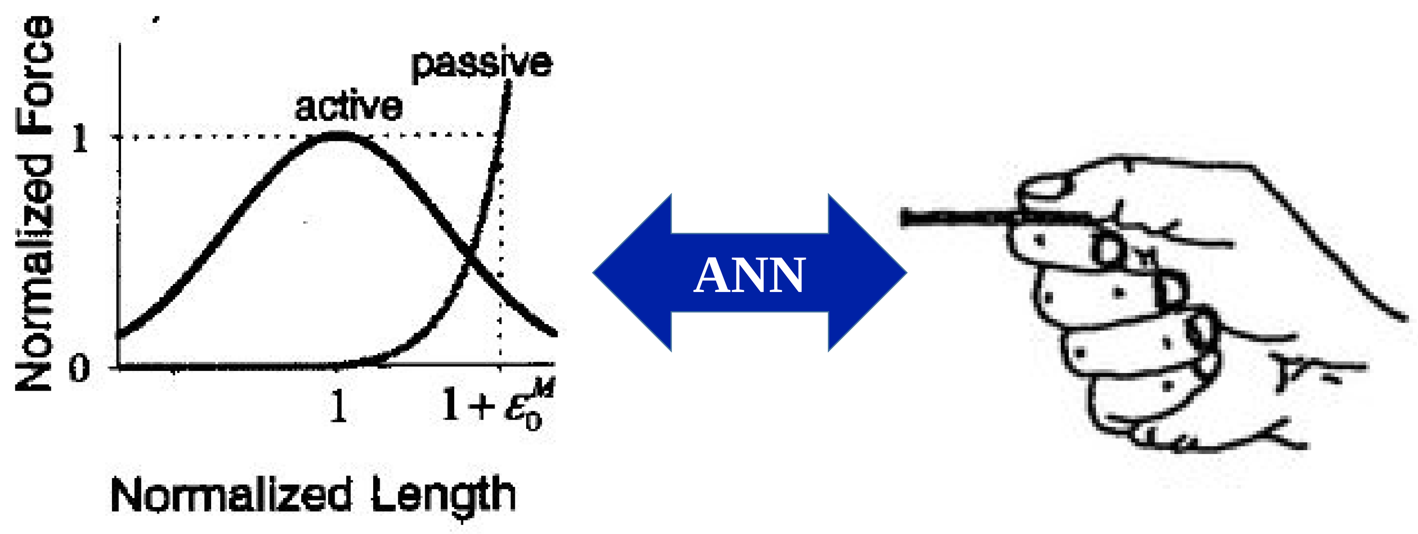
Introduction

- **Current musculoskeletal models of the thumb rely on the estimation of over 109 parameters** defining joint motion, muscle and bone geometry, and muscle architecture.[1]
- Many parameters are **difficult or impossible to measure *in vivo***, impeding development of subject-specific models and interventions.
- **Artificial neural networks (ANN) may be an effective tool for predicting difficult-to-measure parameters.**

Maximum isometric force is the peak of the normalized muscle force-length curve (left)[2].

Lateral (key) pinch is a clinical outcome measure and activity of daily living (right)[3].



Objectives

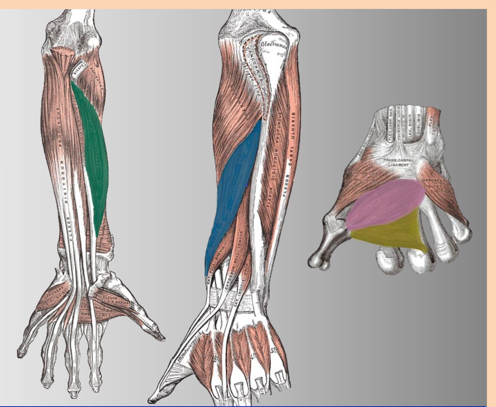
1. **To explore the impact of muscle parameters on thumb-tip force production.**
2. **To identify the need to account for long-term temporal dependencies when mapping muscle parameters to the forces they produce.**

Methods

Dataset Generation

- **Model**: Wrist and Thumb[1]
- **Parameter altered**: Maximum Isometric Force
- **Muscles altered**: *flexor pollicis longus* (FPL), *abductor pollicis longus* (APL), transverse and oblique heads of the *adductor pollicis* (ADPt and ADPo, respectively)

Dataset 1. FPL	**Dataset 2.** FPL, APL
Dataset 3. FPL, APL, ADPt	**Dataset 4.** FPL, APL, ADPt, ADPo

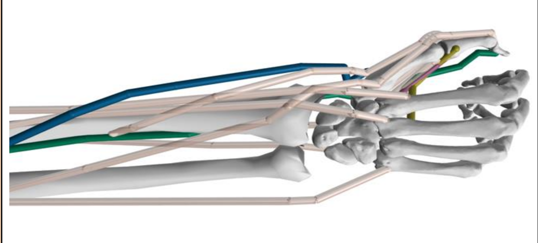


Muscles altered for each dataset (left) and their anatomical location (right).[6]

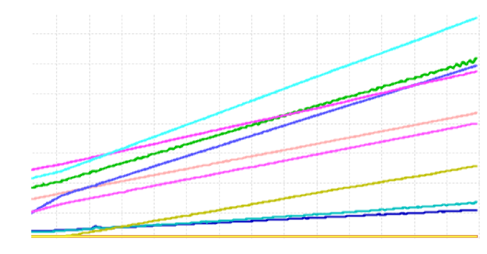
Model Parameters: Vary max iso. force of muscles assoc. with Datasets 1-4.

Target Force (35 N palmar, 10 N ulnar) & Target Posture

Musculoskeletal Model



Muscle Activations



Forward Dynamic Simulation

Thumb-tip Force

Joint Posture

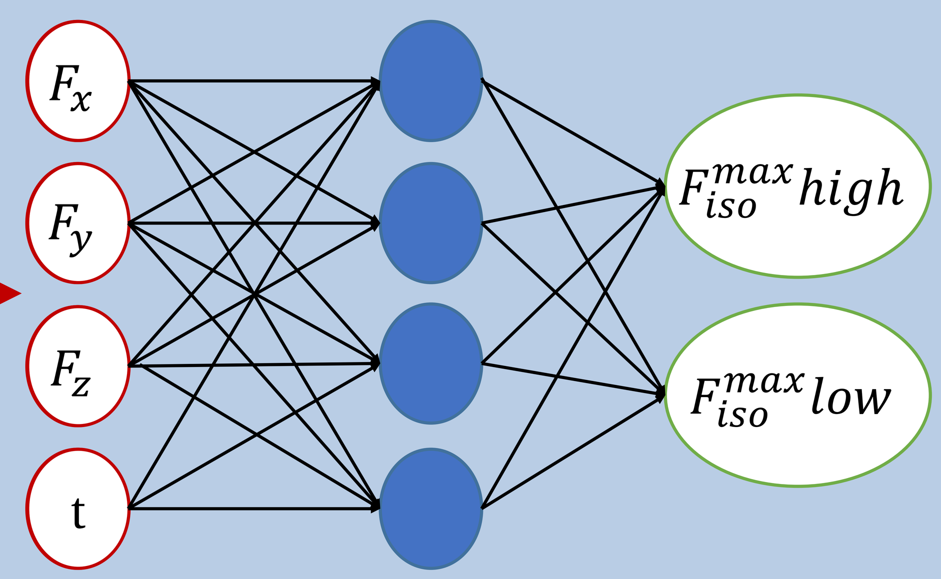
* Associated with Datasets 1-4

Machine Learning

Feed Forward
- Simple
- Lack feedback (i.e. lack "memory")

LSTM
- Type of recurrent neural network
- Has long-term "memory"

Both architectures
- Learning Rate Tuning
- 5-Fold Cross Validation
- Cross Entropy Loss
- Adam Optimizer



Inputs
- Thumb-Tip Force Component Vectors (F_x, F_y, F_z)
- Simulation time (t)

Hidden Nodes

Outputs
- Predicted Max Iso Force (F_{iso}^{max} high, F_{iso}^{max} low)
- 2, 4, 8, and 16 nodes for Datasets 1-4, respectively

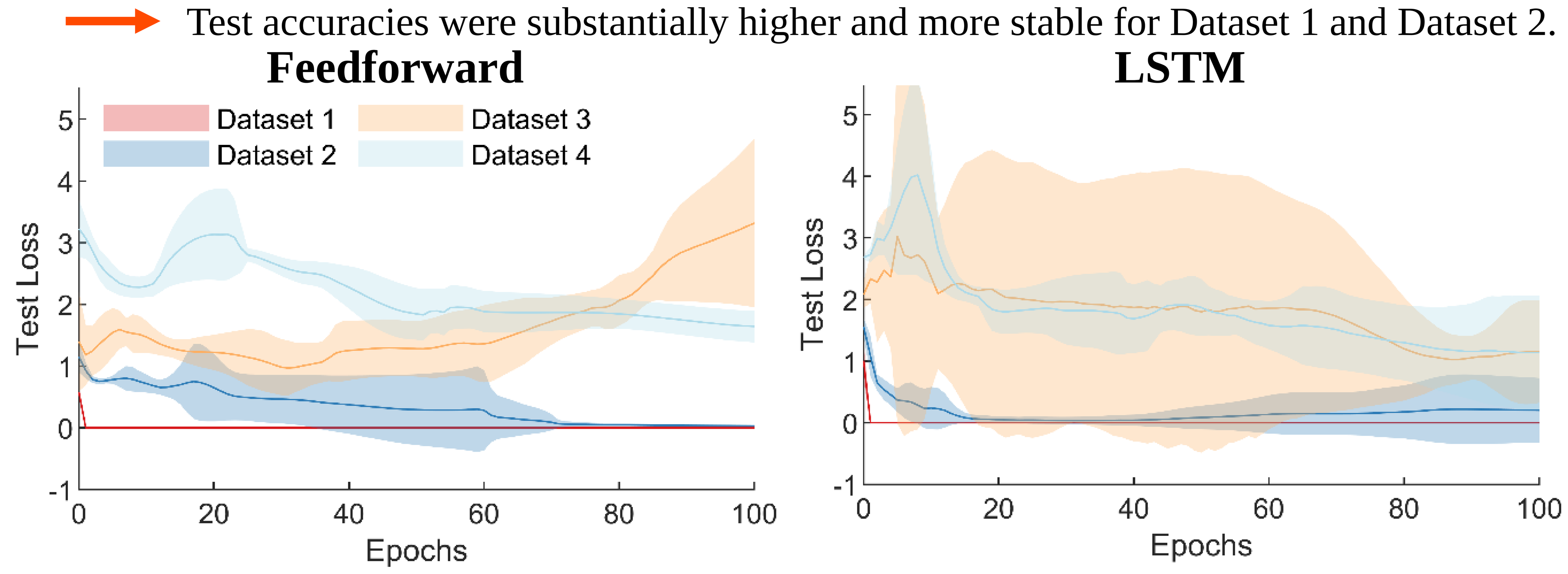
Results & Discussion

Two Key Findings

1. **Under relatively simple conditions, neural networks can classify maximum isometric force from lateral pinch data**

→ Test losses were substantially lower and more stable for Dataset 1 and Dataset 2.

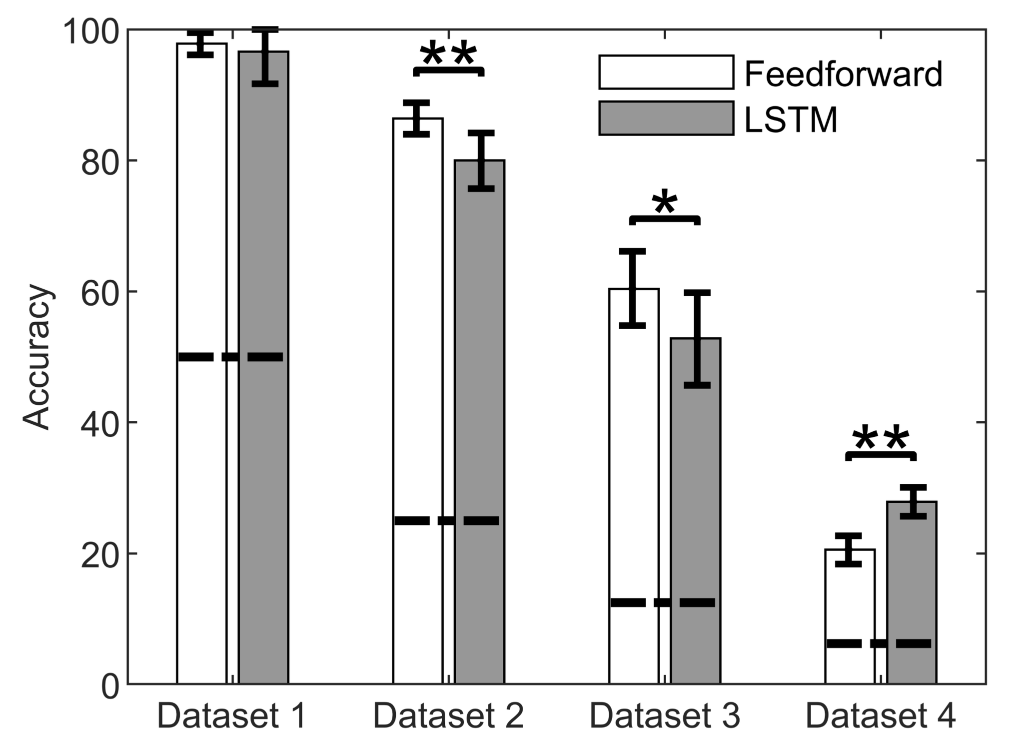
→ Test accuracies were substantially higher and more stable for Dataset 1 and Dataset 2.



Shaded regions represent 95% CI

2. **Accounting for long-term temporal dependencies did not significantly improve ANN performance**

- All models performed substantially better than random guess (represented by the dashed horizontal line)
- Two-sample t-tests showed significant differences between accuracies, but neither model consistently outperformed the other



Error bars represent 95% CI, * and ** denote significance p<0.05 and p<0.01, respectively

Take-Aways:

1. ANNs may be used to predict difficult-to-measure muscle parameters but performance with deeper and wider networks should be investigated.
2. Accounting for temporal dependencies is unnecessary for classifying muscle parameters involved in lateral pinch.

Future Work

- Evaluate performance with **deeper and wider networks.**
- **Classify or regress additional muscle parameters,** such as pennation angle.
- Expand to **more complex motor tasks and biomechanical datasets.**

→ LSTMs may be better suited for predicting muscle parameters for more dynamic tasks, such as gait.

Leveraging simulations and artificial neural networks, we may produce subject-specific musculoskeletal models more accurately.

The present work has been detailed in a manuscript and accepted for publication in PLOS One.

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References

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