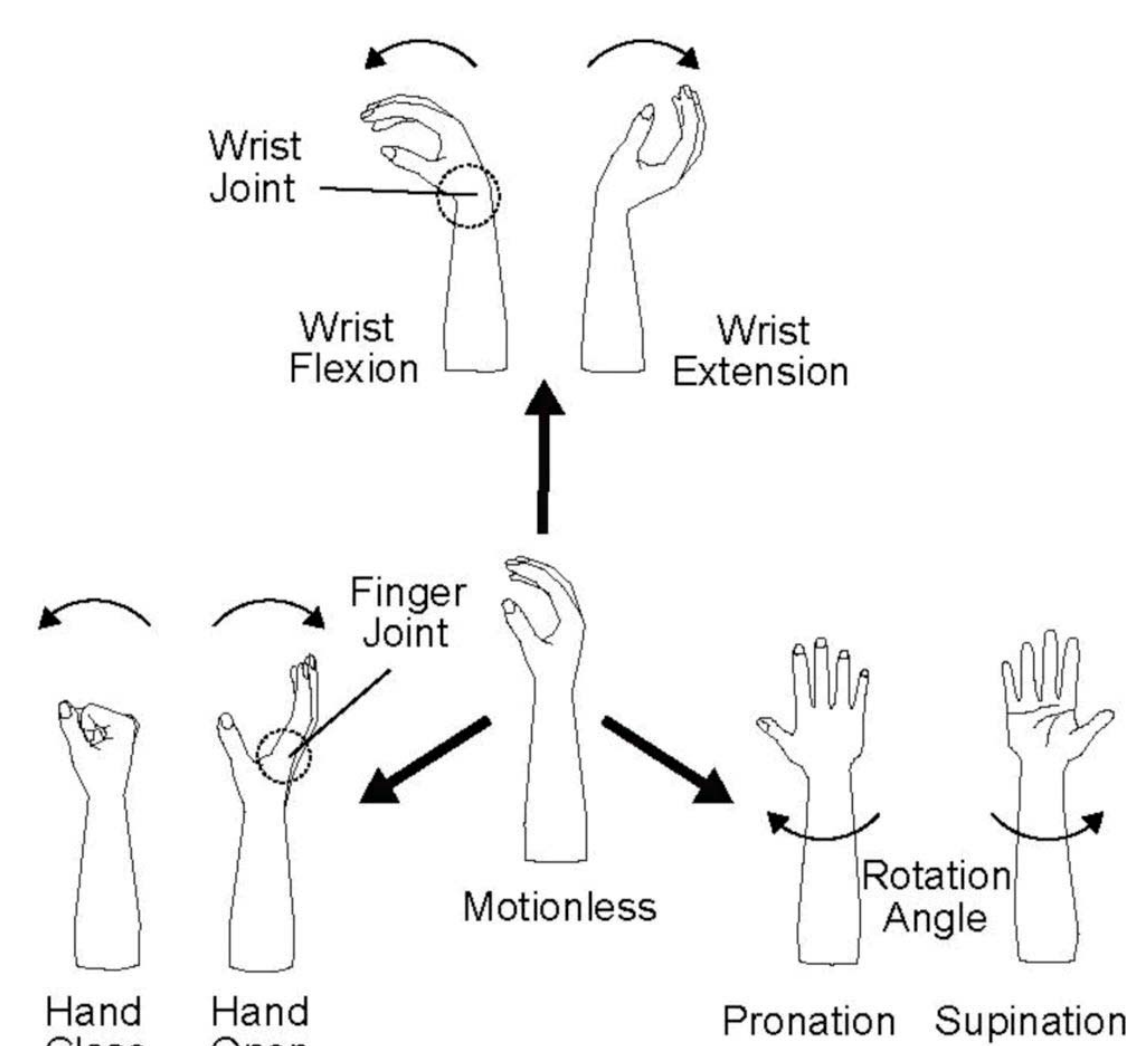
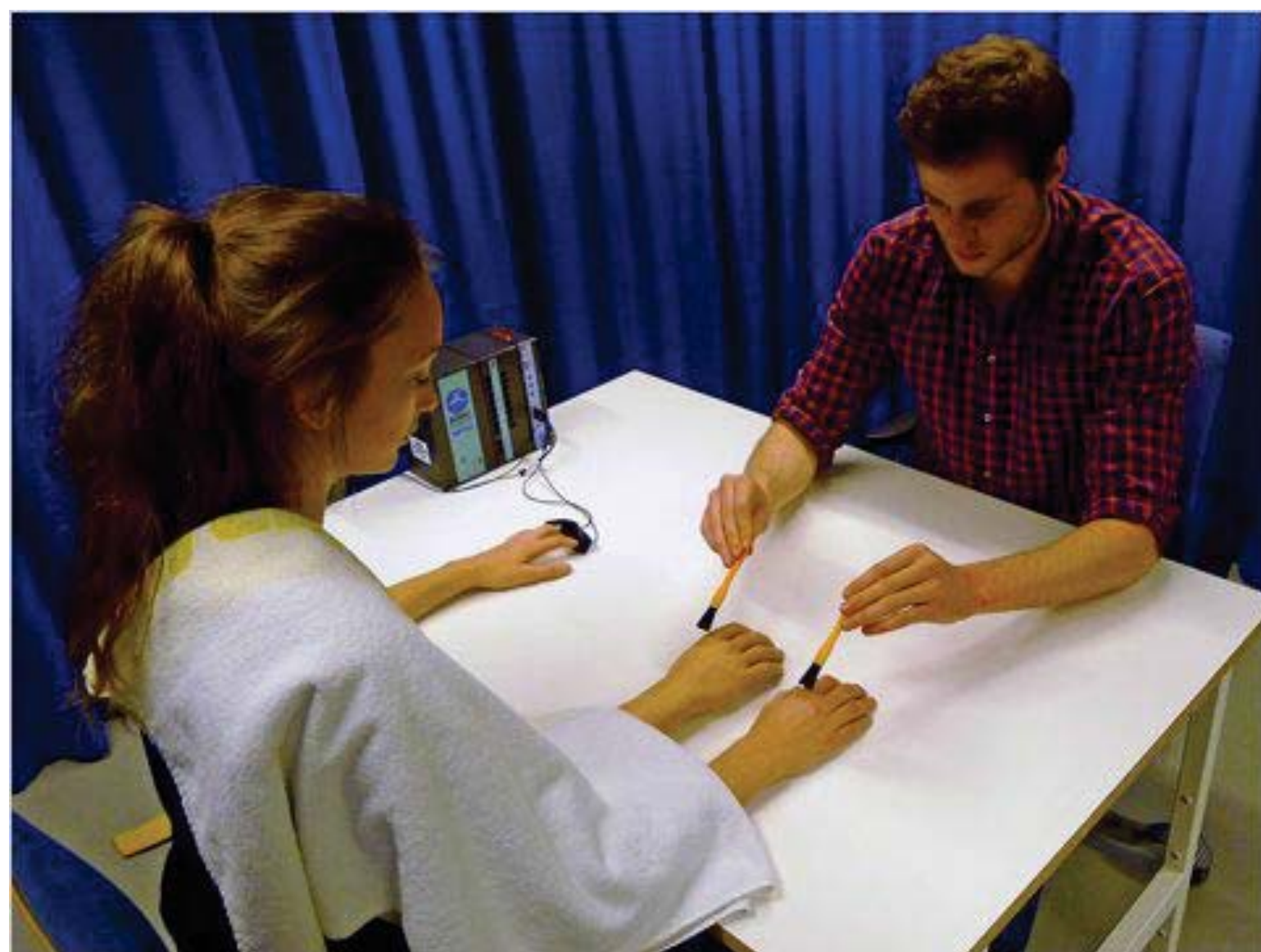




Motivation

- Game-based rehabilitation has a positive short-term effect on EMG (Electromyography) controllability.
- Research has shown that human brain “adopts” fake arm.
- Impact of Quality of Experience on rehabilitation has been proven, though has not been quantified yet.



Goals

- Help amputees with the adoption of their fake i.e., prosthetic arm.
- Collect myoelectric hand movement data from healthy users and use Transfer Learning to predict the hand movements for amputees.
- How to manage disparity between training data and testing data in non-ideal conditions?
 - Limb positions, user’s arm size, placement of sensors

Data Collection

- Get an approval from the CMU Institutional Review Board to collect data from participants.
- 20 Participants were recruited from word of mouth and were paid a \$20 Amazon Gift card.
- Procedure is made up of a pre-game, game and post-game section.
- Around 30 minutes per user, doing all different hand actions.

Architecture

- **Prosthetic Arm** with our embedded sensors to capture the myoelectric signals from the users’ arm.
- **Machine Learning Layer** to predict the gestures of the users.
- **Cloudlet** to infer from the machine learning model while providing low latency.
- **Unity Framework** used to translate user actions into various in-game actions.
- Supported games include 1942 and Flappy Bird, which are easily extensible into any other game.
- 7 Hand Motions as labels to control the game
 - Resting, Hand Open, Hand Close, Supination, Pronation, Wrist Flexion, Wrist Extension



Fig: Data Collection Screen (Left) and 1942 Game Screen (Right)

Machine Learning Layer

- (1) **Machine Learning**
 - Feature Extraction of TDD and TSD Domain features on 1000 Hz high frequency data
 - Training random forest with 300 d-trees and grid search for optimal parameters
 - Noise Reduction with Butterworth Filter and Dimensionality Reduction with PCA as additional optional steps
- (2) **Deep Learning:**
 - LSTM model working on 40 Hz data
 - Using a raw sEMG image with 200 x 8 values
 - Making use of temporal and spatial knowledge from data
 - Main challenge: robustness to user-wise changes

Analysis

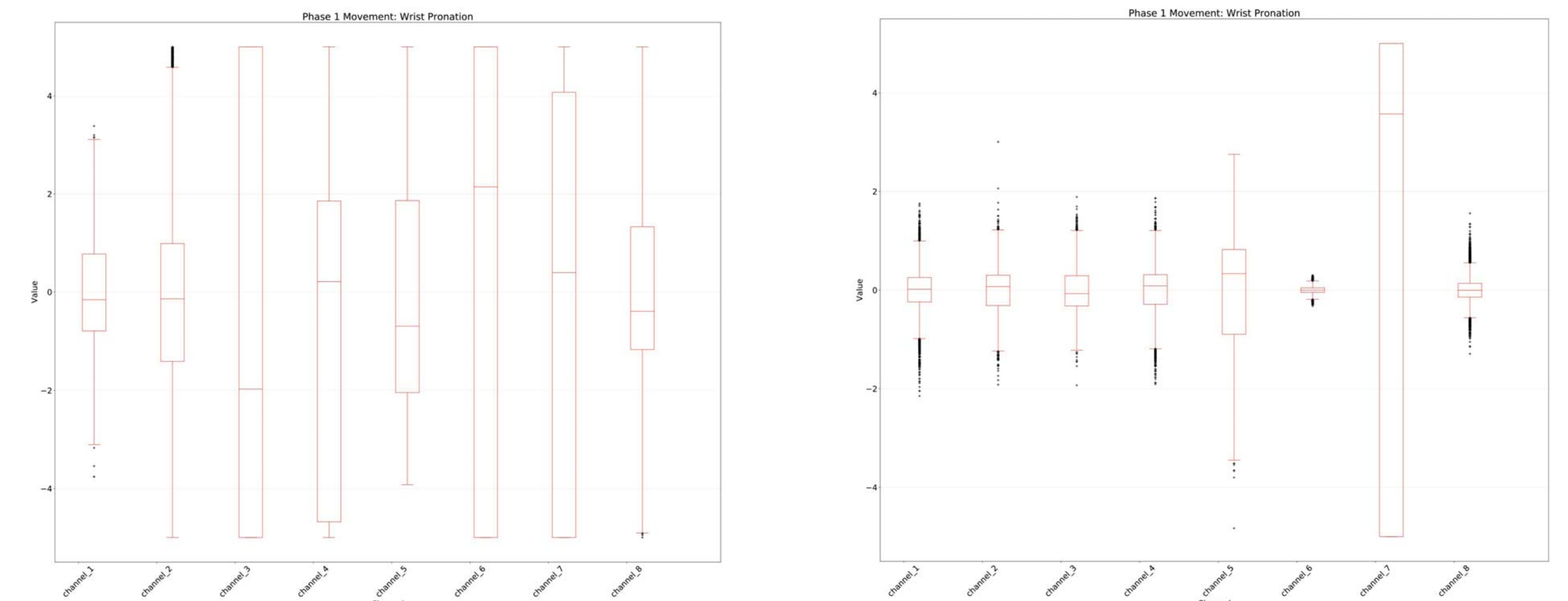


Fig: Raw Data from two different Users

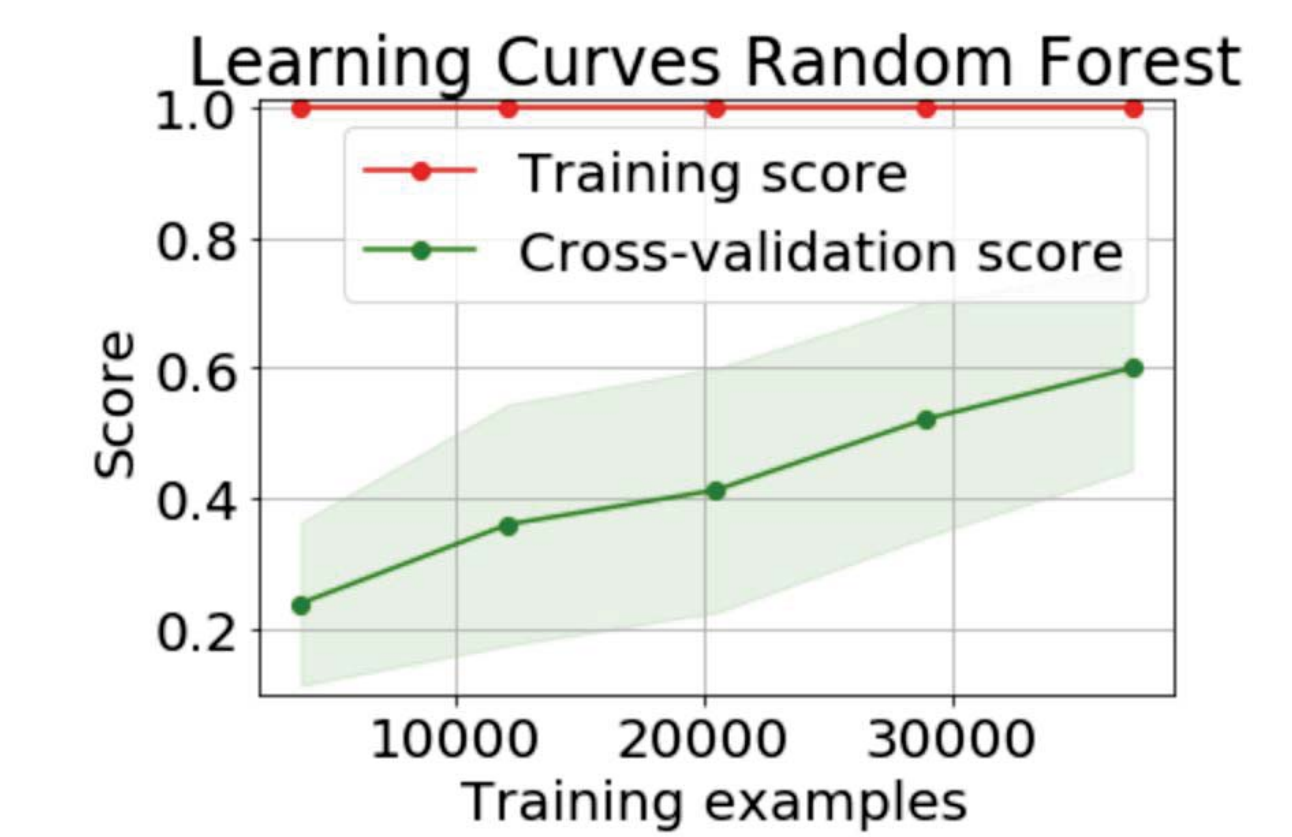


Fig: Learning Progression using Random Forest

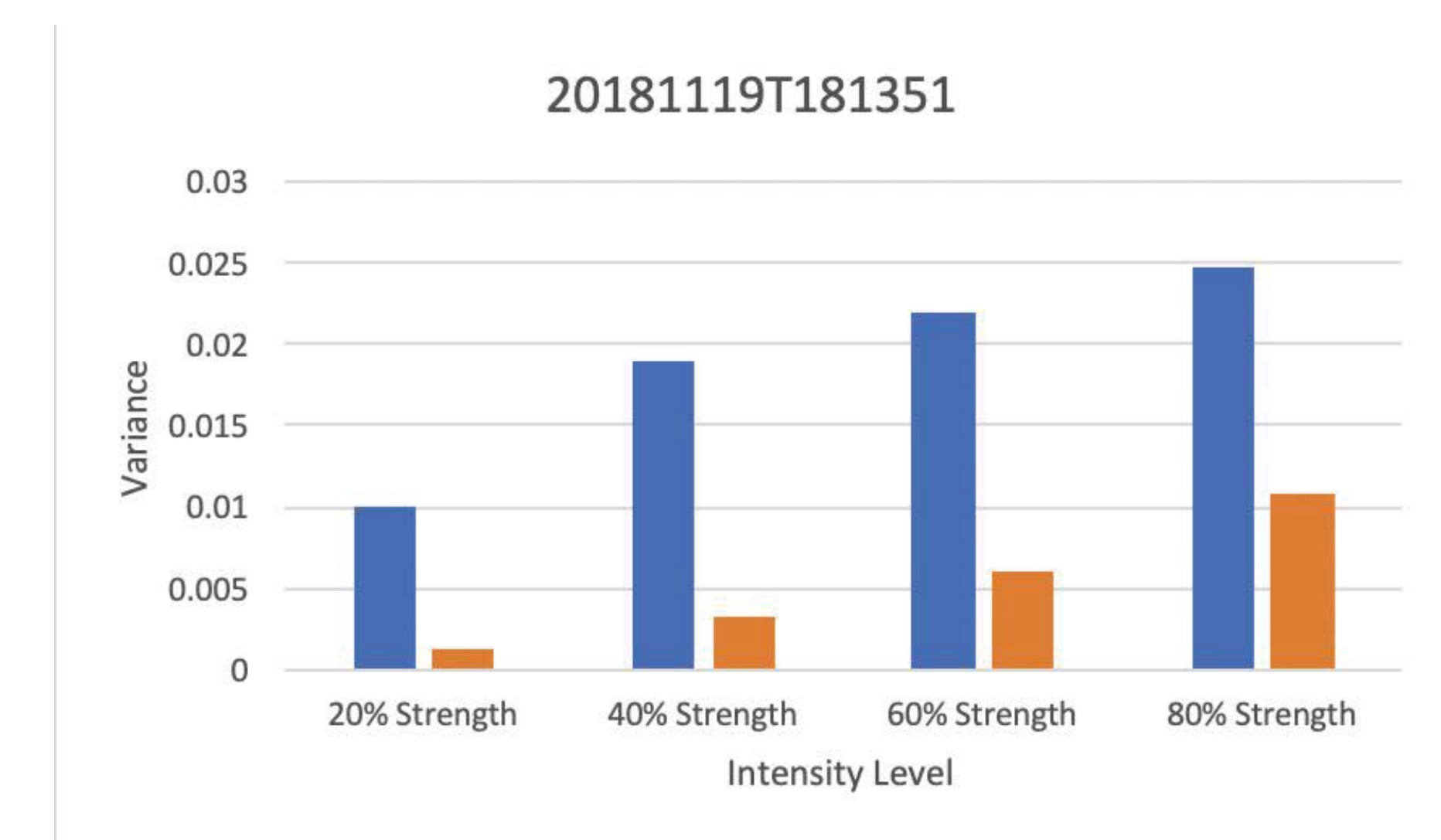


Fig: Before- vs. Aftergame ability to hold contraction intensity level

Future Work

- Collect more data in a more diverse set of conditions.
- Try newer Machine Learning and Deep Learning techniques to get better accuracy.
- Test on amputees and verify the transfer learning

References

- <https://well.blogs.nytimes.com/2011/02/24/need-an-extra-hand/>
- Rami Khushaba, et al. A Framework of Temporal-Spatial Descriptors-Based Feature Extraction for Improved Myoelectric Pattern Recognition <https://doi.org/10.1109/>