Feasibility of Using Low-End Wearable Armbands and Unsupervised Transfer Learning for Seamless Myoelectric Control

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HIGHLIGHTS:

1. **Robust performance and seamless usability are crucial for intuitive HMI with myoelectric control.**
2. **We tested feasibility of using a low-end wearable sensor combined with unsupervised transfer learning.**
3. **Proposed approach improves accuracy across various measurement conditions without recalibration.**
4. **This framework is feasible and promising for seamless myoelectric control in rehabilitation robotics.**

INTRODUCTION

Myoelectric control uses electromyography (EMG) signals as human-originated input to enable intuitive interfaces with machines.

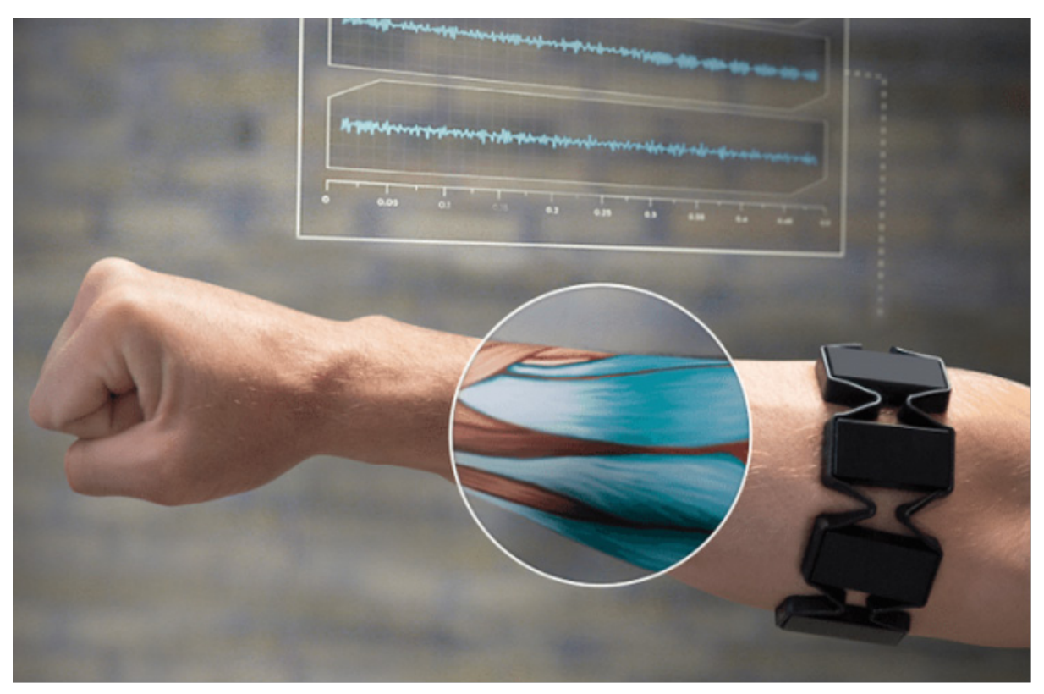
- Recent rehabilitation robotics employs myoelectric control to autonomously classify user intent or operation mode using machine learning.
- However, performance in such applications inherently suffers from the non-stationarity of EMG signals across measurement conditions. Current laboratory-based solutions rely on ***careful, time-consuming control of the recordings or periodic recalibration***, impeding real-world deployment [1].

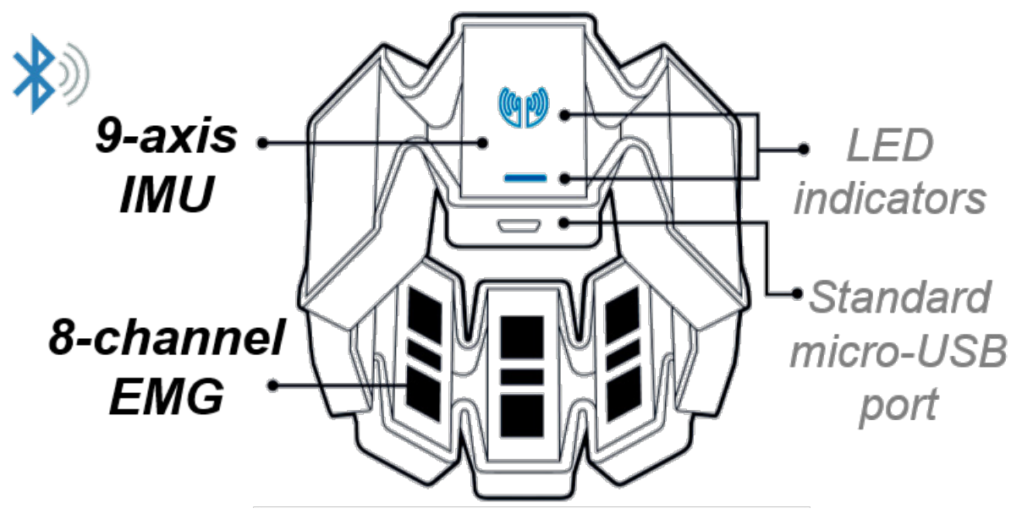
We propose that robust yet seamless myoelectric control can be achieved using a low-end, easy-to-"don" and "doff" wearable sensor combined with unsupervised transfer learning.

APPROACH

Here, we tested the feasibility of one such application using a consumer-grade armband sensor for robust gesture classification across various measurement conditions.

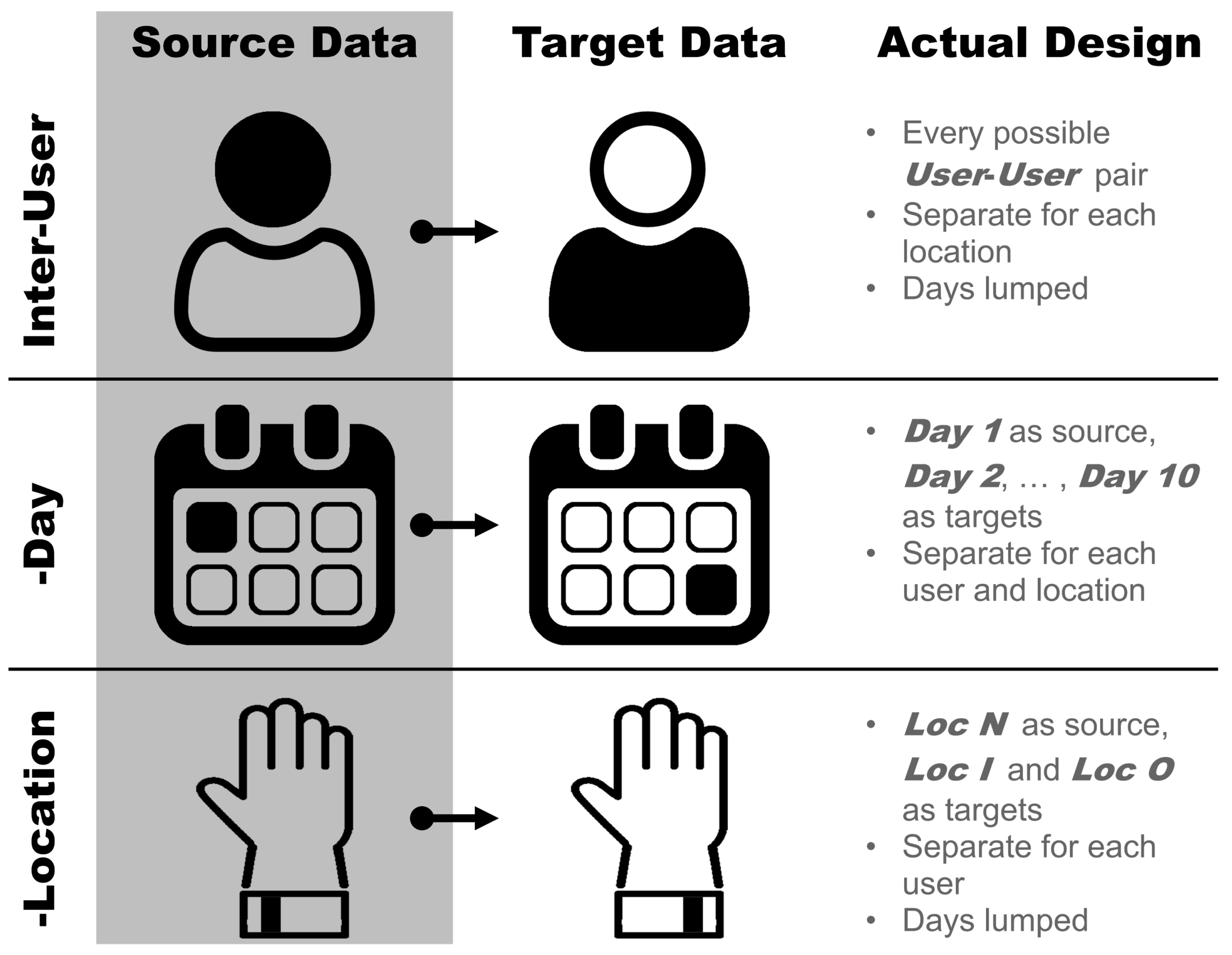
- Device:
  Myo armband,
  8 EMG channels @ 200 Hz
- Dataset (from [2]):
  5 users x 10 days x
  3 wearing locations
  (**N**eutral, **I**nward- and **O**utward rotated)
- Gestures:
  22 wrist and hand gestures
  (8 1-DoF and 14 2-DoF) [3]





We adopted an unsupervised domain adversarial self-calibration algorithm for transfer learning.

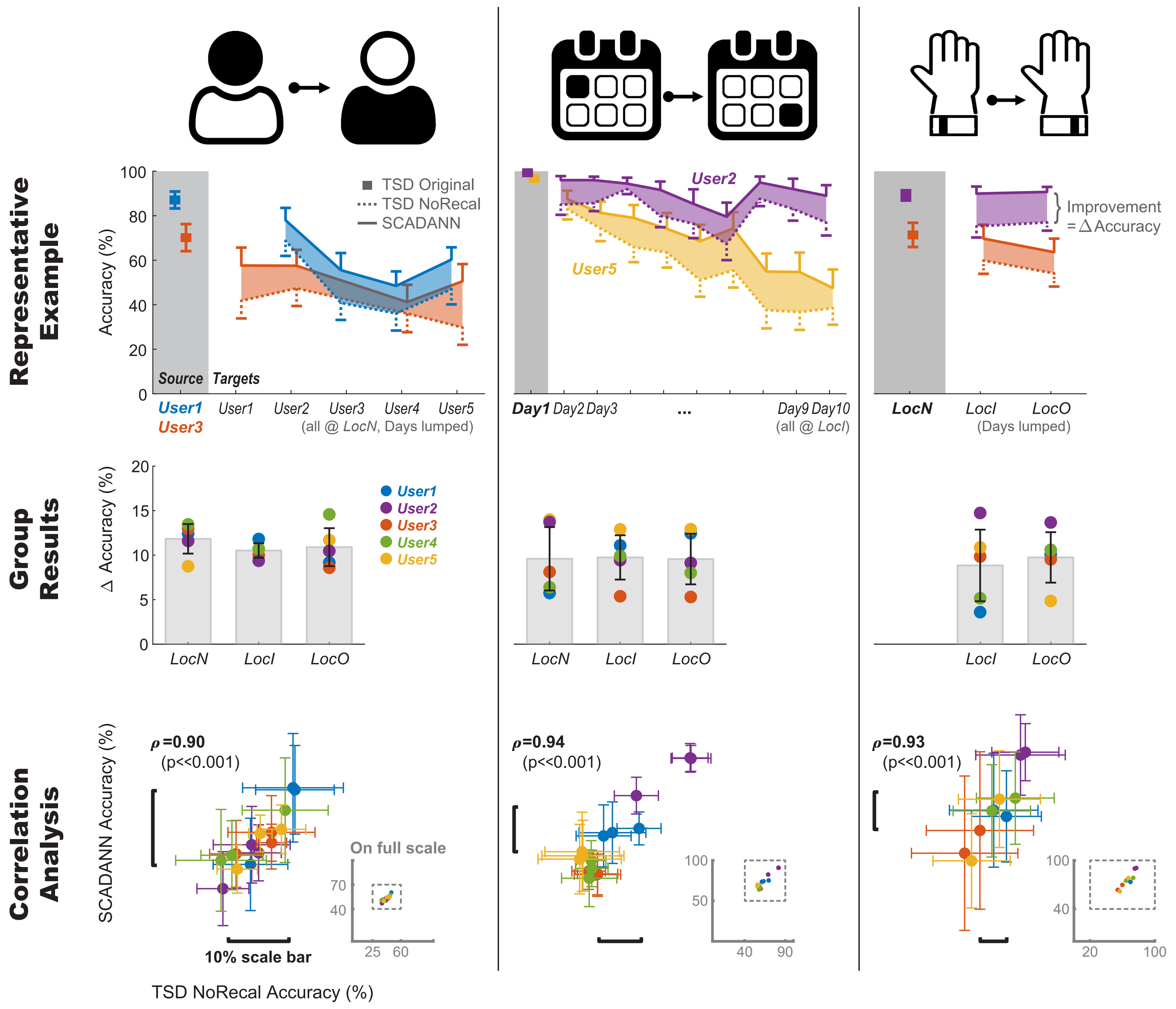
1. Train a deep neural network using Temporal-Spatial Descriptors (TSD) [4] with labeled ***Source Data*** from any particular user, day, or location.
2. Self-Calibrating Asynchronous Domain Adversarial Neural Network (SCADANN) [5] automatically adjusts the trained TSD to improve classification performance for unlabeled ***Target Data*** from a different user, day, or location.



	Source Data	Target Data	Actual Design
Inter-User			Every possible ***User-User*** pair Separate for each location Days lumped
-Day			***Day 1*** as source, ***Day 2***, … , ***Day 10*** as targets Separate for each user and location
-Location			***Loc N*** as source, ***Loc I*** and ***Loc O*** as targets Separate for each user Days lumped

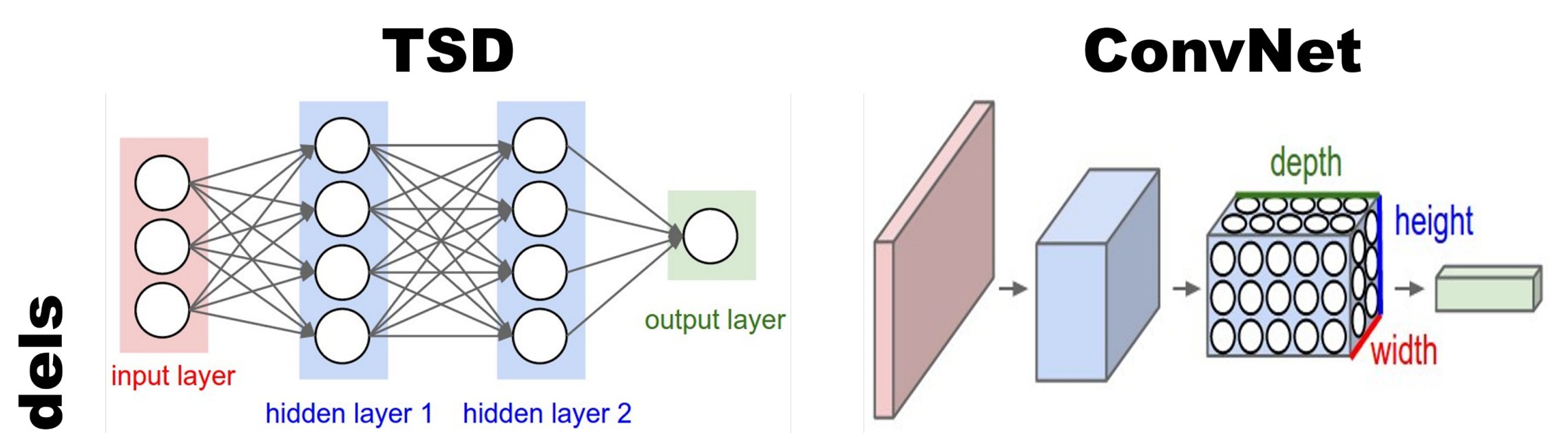
RESULTS

1. Transfer learning (e.g., SCADANN) can improve accuracy across various measurement conditions (inter-user, -day, -location), without the need to recalibrate.



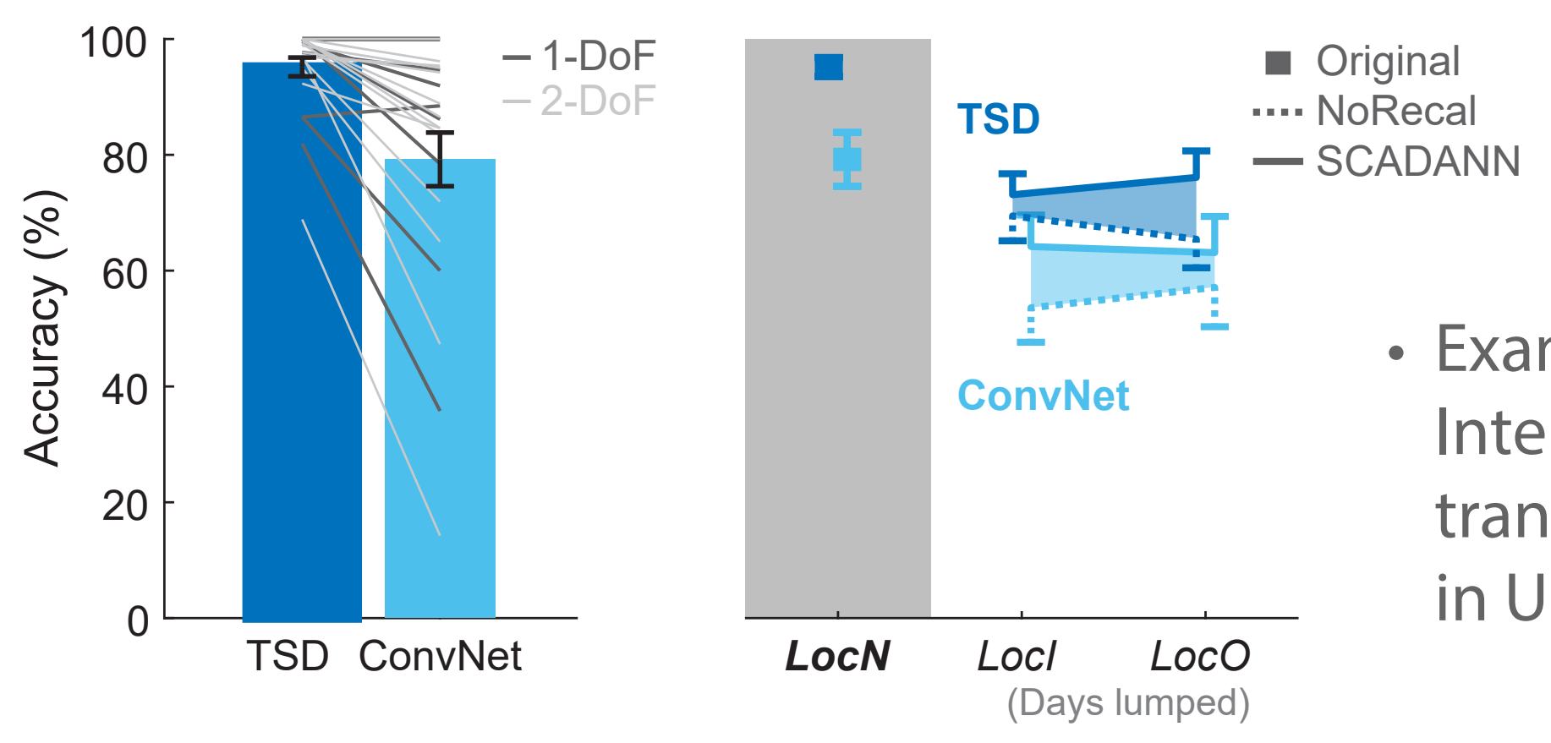
- In one best-case scenario, accuracy improves by 26% (from 67% to 93%), whereas sometimes the gain is modest (e.g., from 76% to 78%)
- SCADANN improves accuracy by 12±5.2% (avg±sd), 9.6±5.0%, and 9.3±3.5% across all user-to-user, day-to-day, and location-to-location cases, respectively.
- Cross-over accuracy of original TSD trained with source data dictates SCADANN performance, which implies that we need a ***"good" model, trained with "good" source data*** to begin with!

2. A) Better selection of initial model (e.g., TSD vs ConvNet) and B) Training that model with incremental source data can improve performance of transfer learning (e.g., SCADANN).



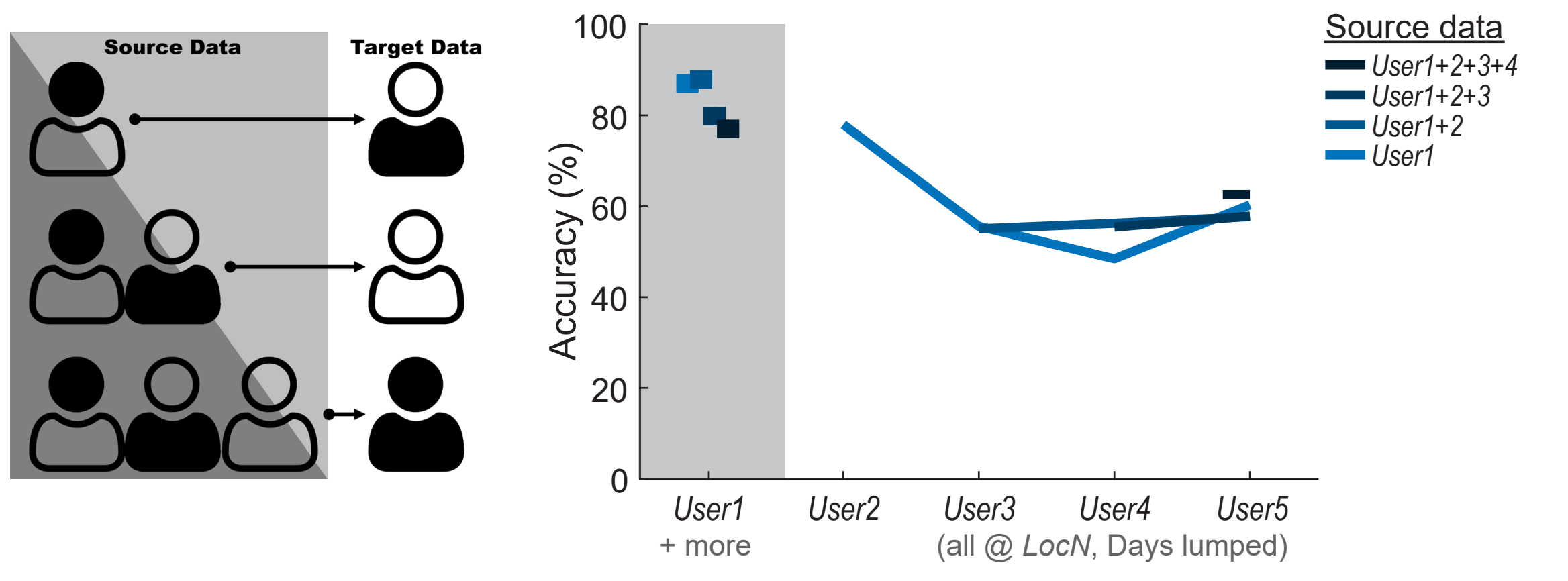
- Small and simple DNN
- 3 fully connected layers (batch normalization → leaky ReLU), each 200 neurons wide
- Input: 252 temporal-spatial descriptors

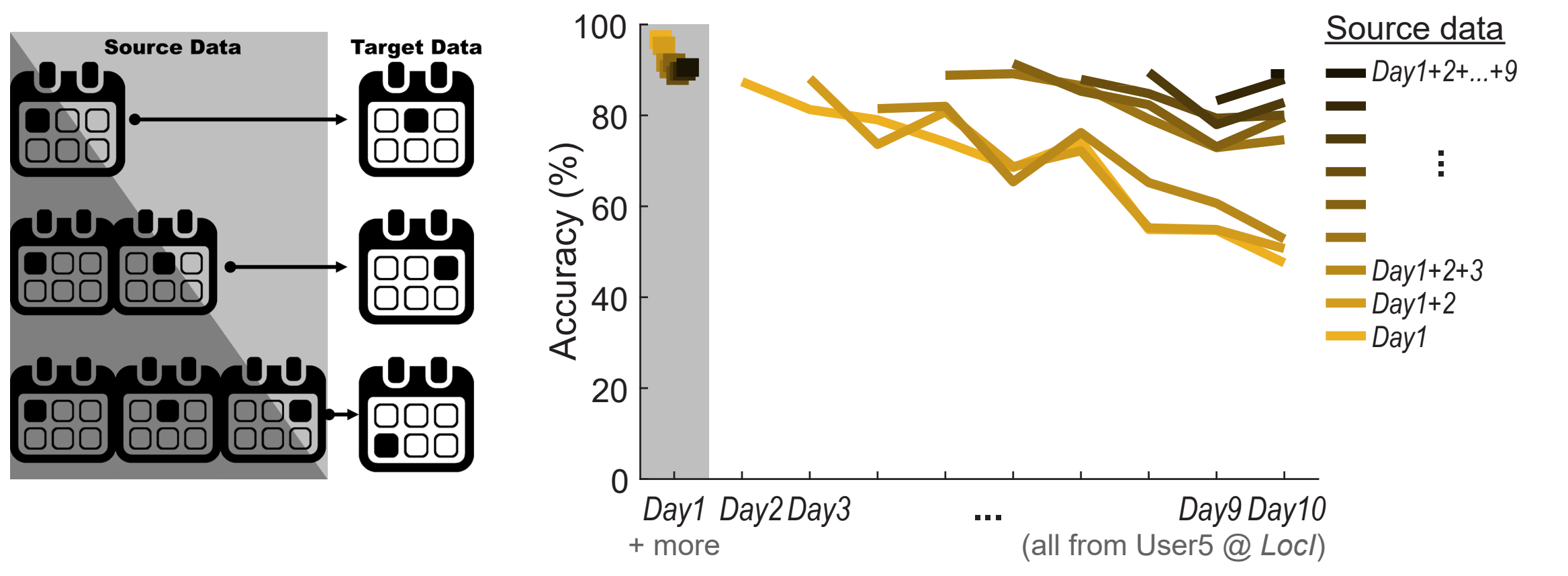
- Small and simple CNN
- 4 blocks (each block: convolutional layer → batch normalization → leaky ReLU → dropout) → global average pooling → two heads
- Input: 4x8x10 spectrograms



- Example: Inter-location transfer learning in User1

- TSD performs better than ConvNet [5], both for the source data (left) and when transferred to target data with SCADANN (right).





- Cumulatively including data from more users (top) or days (bottom) tends to improve performance for new target data.
- Incremental source data from "ideal" combination of only a few datasets may be more efficient than repetitive recalibration.

CONCLUSIONS

The proposed approach is feasible and can be further tailored.

- Comparable (or better) performance (i.e., improvement in accuracy) to similar approaches [5-7], even with no parameter optimization and a limited data set
- More rigorous validation: Training, calibration, validation, testing
- Combined effects of transfer learning across contexts (e.g., user x day)

The proposed approach is promising for seamless myoelectric control of powered prosthetics or exoskeletons.

References

1. Ketykó et al., 2019, IJCNN
2. Kanoga et al., 2020, Biomed Sig Process & Control
3. Muceli & Farina, 2012, IEEE TNSRE
4. Khushaba, et al.,2017, IEEE TNSRE
5. Côté-Allard et al., 2020, IEEE Access
6. Kanoga et al., 2021, Biomed Sig Process & Control
7. Côté-Allard et al., 2021, IEEE TNSRE

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